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Data-driven virtual sensor systems for dynamic temperature monitoring along food supply chains

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ABSTRACT

Continuous monitoring of perishable food temperatures along supply chains is crucial for quality assurance and reducing food loss and waste. However, cost and installation constraints restrict sensor deployment, compromising the reliability of temperature monitoring. This study proposes a data-driven virtual sensor system that leverages deep learning to integrate multi-source data, enabling temperature estimation at sensor-inaccessible locations and thus reducing dependence on extensive physical sensor deployment. The system was evaluated across postharvest processing, storage, and transport. Results indicate that, with a fixed number of physical sensors, increasing the virtual-to-physical sensor ratio from 16 to 32 maintains the root mean square error below 0.3 °C. Further analysis shows that sensor placement within pallets has minimal impact on performance, whereas the choice of data sources and model architecture exerts a significant influence. Notably, a configuration of one sensor per pallet with a BiLSTM + attention model outperforms shallow networks, demonstrating the potential of data-driven virtual sensor system to enhance temperature monitoring and efficiency along food supply chains.

Nomenclature

ANN	Artificial neural network
BP	Backpropagation
BS	Baseline scenario
CNN	Convolutional neural network
DD-VSS	Data-based virtual sensor system
ERR	Equivalent replacement rate
FSC	Food supply chain
IAT	Internal ambient temperature
IFT	Initial food temperature
LSTM	Long short-term memory
MAE	Mean absolute error
PB-VSS	Physics-based virtual sensor system
PSS	Physical sensor system
RMSE	Root mean square error
RNN	Recurrent neural network
SAE	Stacked autoencoders
TFP	The temperature of the food on pallet
VSS	Virtual sensor system

1. Introduction

Temperature is widely recognized as a critical determinant of perishable foods quality and safety (Zhou et al., 2025; Ziegler et al., 2021). Continuous monitoring of temperatures along the food supply chain (FSC) is essential for monitoring food quality and minimizing losses (Göransson et al., 2018). In addition to enabling effective quality monitoring, dynamic temperature monitoring facilitates accurate estimation of the remaining shelf-life of perishable items (Buisman et al., 2019; Olawale et al., 2025). This shelf-life information can be leveraged to optimize supply chain operations, including first-expired, first-out inventory management, dynamic shelf-life tracking, and pricing strategies (Waldhans et al., 2023; Zhang et al., 2024). Consequently, integrating temperature-based management practices enhances resource utilization, strengthens food safety, improves food supply reliability, and mitigates the environmental impacts of food systems (Anukiruthika and Jayas, 2025; Gatto and Chepeliev, 2024).

Significant challenges remain for large-scale commercial deployment of temperature monitoring systems along the FSC (Jedermann et al., 2017; Wei et al., 2024), with cost being a primary constraint.

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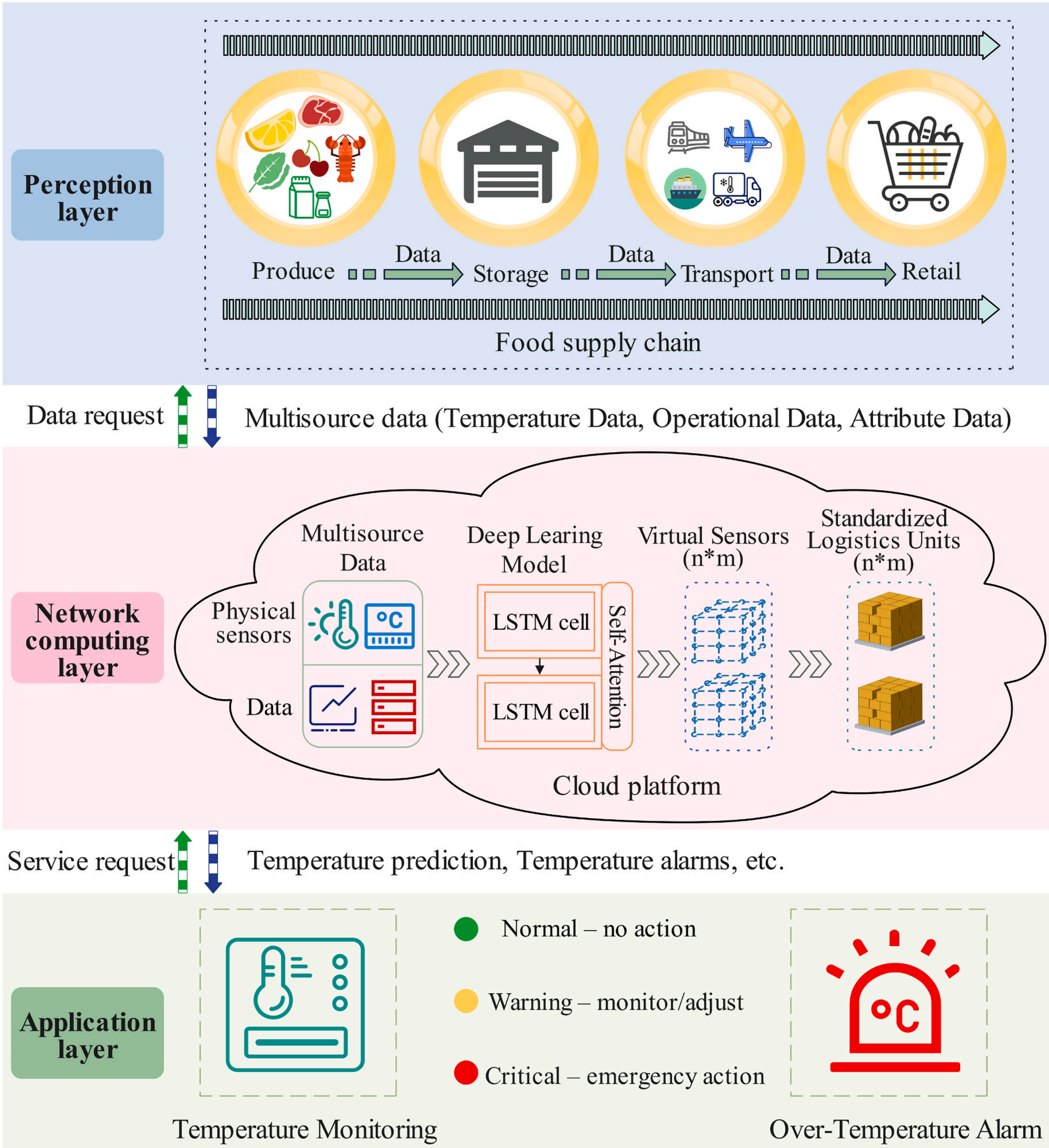

Fig. 1. Framework for data-based virtual sensor systems along the food supply chain.

High-resolution monitoring requires numerous physical sensors, as different batches of perishable foods may experience heterogeneous time-temperature profiles due to variations in ambient conditions, port delays, route changes, and potential refrigeration failures (Li et al., 2025; Schudel et al., 2023). For example, fruit cooling rates can vary by up to 42 % between packages (Wu et al., 2018a). For comprehensive temperature mapping in refrigerated containers, 20 to 30 sensors are typically required (Jedermann et al., 2011), and global long-distance transport could demand approximately 1 billion sensor modules, assuming one sensor per 100-L container (Zhu et al., 2022). In practice, high-value perishables (e.g., Bluefin tuna) are monitored densely, whereas low-value items often receive minimal sensor coverage, reflecting economic constraints in sensor deployment (Musa and Dabo, 2016). Moreover, most refrigerated containers track ambient rather than food temperatures (Yu et al., 2024), which can introduce substantial management errors because food temperatures are highly heterogeneous relative to the surrounding environment (Badia-Melis et al., 2016; Shrivastava et al., 2022).

Beyond financial constraints, the effectiveness of temperature monitoring is also limited by sensor deployment locations (Abdollahzadeh and Navimipour, 2016). In refrigerated trucks, for instance, ambient temperature sensors are often installed on the ceiling of the carriage for logistical convenience, but this configuration can compromise measurements accuracy (Laguerre et al., 2015). Mercier and Uysal (2018) demonstrated that positioning sensors at the corners of pallets yields higher information content, as these locations show strong correlations with other points within the pallet and thus improve estimation accuracy. Nevertheless, determining optimal sensor placements for different cold chain infrastructures—or directly monitoring each box within a pallet—remains impractical in large-scale commercial operations.

A promising approach to overcoming these is the development of

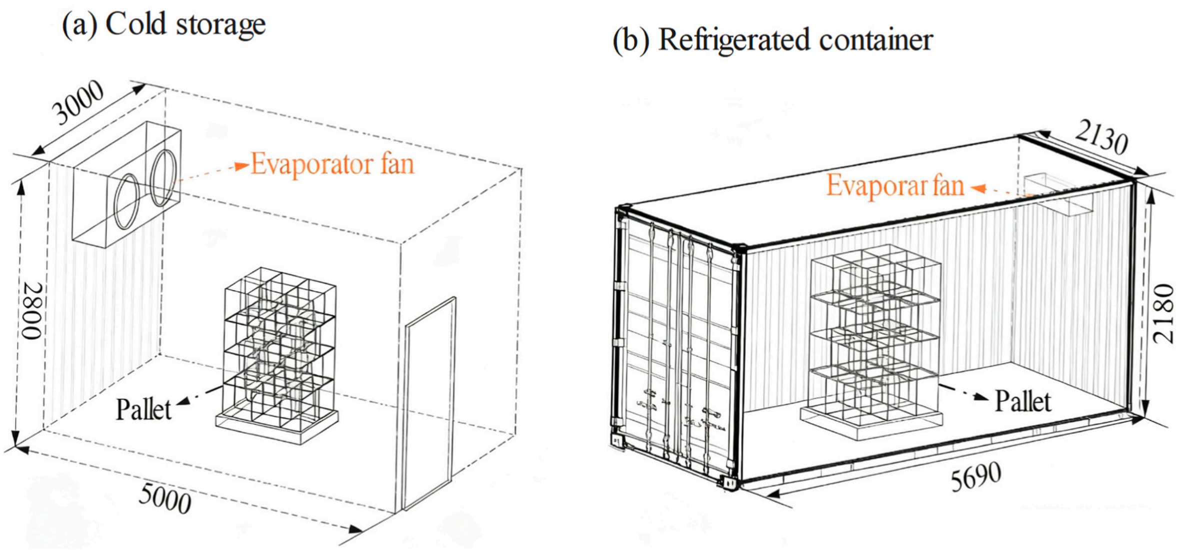

Fig. 2. Experimental equipment: a) Cold storage, used to simulate the postharvest processing and storage; b) Refrigerated container, used to simulate the transport process.

virtual sensor system (VSS) (Wu et al., 2018b) which enable high-accuracy, low-cost temperature monitoring along the FSC by estimating temperatures at unmeasured locations using data from a limited number of strategically placed sensors. VSS are generally classified into physics-based (PB-VSS) and data-driven (DD-VSS) systems (Mercier et al., 2017). PB-VSS employ conservation laws of momentum, heat, and mass to describe transfer processes and have been successfully applied to precooling (Kumar et al., 2023), transport (Defraeye et al., 2015), and storage (Bishnoi and Aharwal, 2020). These models provide detailed insight into temperature distributions within pallets and strengthen understanding of underlying physical mechanisms. However, their practical implementation is constrained by demanding data requirements—such as accurate transfer properties and boundary conditions—as well as the computational burden of airflow modeling and CFD simulations (Defraeye et al., 2019; Laguerre et al., 2013).

In contrast, DD-VSS does not require a comprehensive understanding of the underlying physical principles of the application scenario (Wang et al., 2024; El-Mesery et al., 2025). Instead, it infers target variables directly from measurable data using mathematical and computational techniques. For example, Ragab et al. (2025) developed an IoT-based real-time monitoring system that combined sensor data with hybrid modeling techniques to predict process parameters in friction stir spot welding. Furthermore, the performance of DD-VSS critically depends on the choice of neural network architecture, the calibration of model inputs with training datasets, and validation on independent datasets (King et al., 2024). While DD-VSS may offer less explanatory power regarding physical phenomena compared to PB-VSS (Mercier et al., 2017), their flexibility—stemming from the absence of strict physical constraints—makes them particularly effective in handling complex and highly coupled processes. This advantage is further magnified by the increasing volume and accessibility of IoT data (Huang et al., 2024).

Prior evidence shows DD-VSS can generalize across industries (Choi et al., 2024a, 2024b), whereas work in cold-chain management still centers on physical sensors and TTI-based shelf-life monitoring (Waldhans et al., 2025; Yar et al., 2025). Nevertheless, the heterogeneity of products, routes, and handling practices renders purely physics-based modeling difficult to scale and costly to deploy. In this context, cold-chain monitoring can be reframed as a virtual sensing problem, with operational traces and ambient measurements serving to estimate unobserved temperature.

However, the application of DD-VSS along the FSC remains limited. Existing studies have primarily focused on improving prediction accuracy, while few have explored systems aimed at reducing the number of physical sensors deployed (Badia-Melis et al., 2018). In particular, there is a lack of in-depth research on the unique advantages of DD-VSS for dynamic temperature monitoring, including its marginal benefits and flexibility in sensor layout, and optimal strategies for selecting multisource data and configuring deep learning networks to achieve accurate and cost-effective temperature predictions remain unclear. This study aims to address these gaps by evaluating the capability of DD-VSS to achieve accurate temperature monitoring along the FSC while minimizing physical sensor requirements. Specifically, the objectives are to evaluate and select suitable multisource data, identify effective neural network architectures, assess the influence of sensor placement on predictive performance, and explore the potential for large-scale commercial deployment. To achieve these objectives, experiments were conducted to generate temperature data within food pallets along the FSC, which were subsequently used to train and validate the DD-VSS model.

2. Methodology

A DD-VSS framework based on long short-term memory (LSTM) was developed for efficient temperature management along the FSC. The framework is structured into three layers: the perception layer, the network computation layer, and the application layer (Fig. 1). In the perception layer, multisource data—including temperature, operational, and product-attribute data—are collected and preprocessed before being transmitted to the computation layer. Within the computation layer, temperature estimation is performed using a bidirectional LSTM (BiLSTM) with an attention mechanism. In the application layer, the estimated temperatures are applied to dynamic monitoring, shelf-life estimation, and alert generation by comparing predicted values against predefined thresholds. Through the integrated operation of these three layers, real-time temperature management along the FSC is achieved, thereby enhancing transparency and management efficiency.

2.1. Generation of the multisource data

2.1.1. Cold storage and refrigerated containers

The experiments were conducted in December 2023 and June 2024 at Guangzhou University (Southern China) using a cold storage facility and a refrigerated container to simulate postharvest processing, storage, and transport stages of the citrus supply chain. The cold storage facility

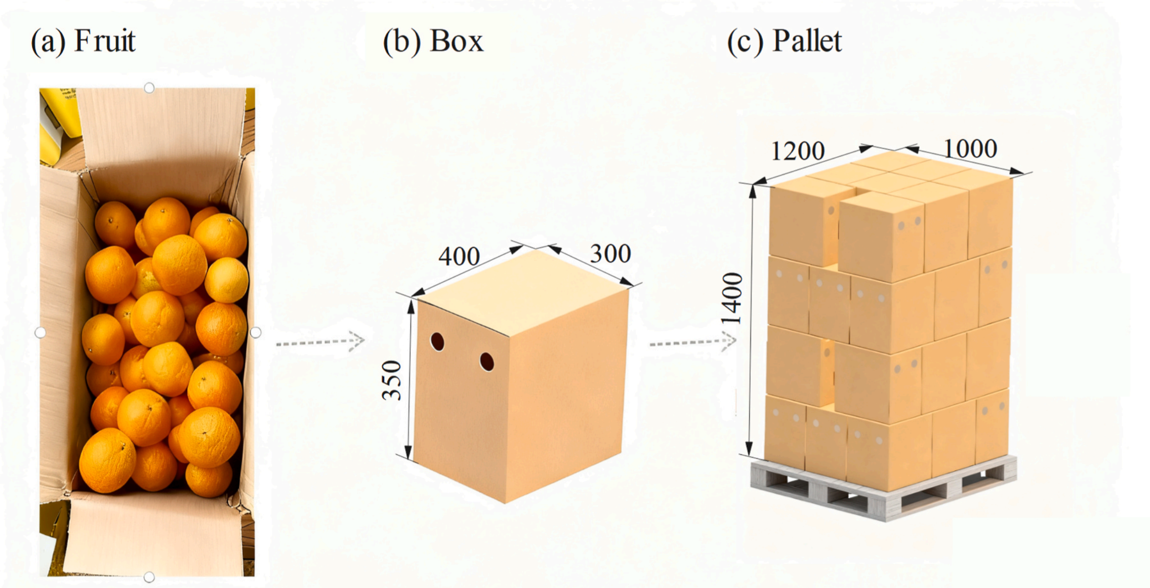

Fig. 3. Packaging levels in the cold chain: fruit, box, and pallet.

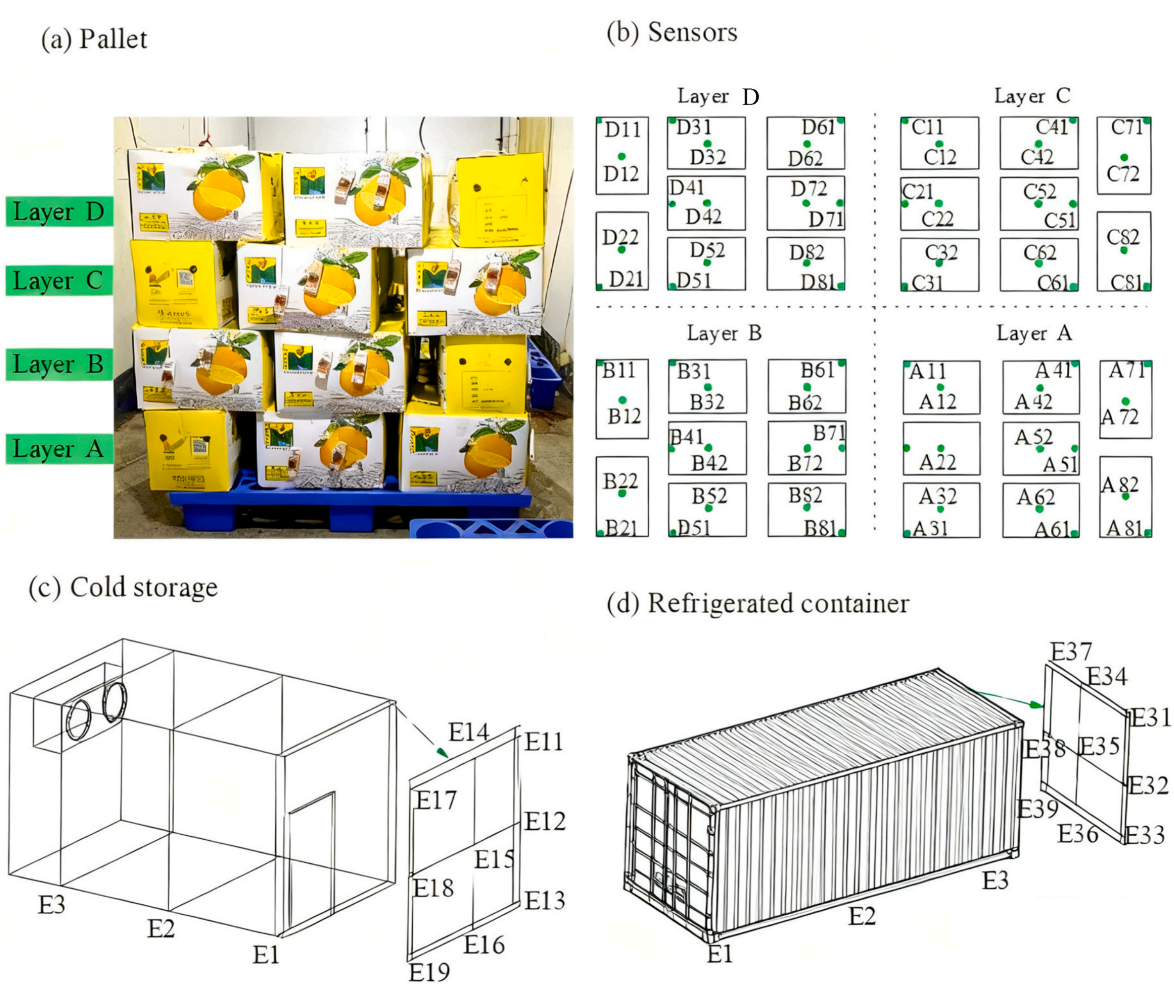

Fig. 4. Sensor Layout: a) Fruit pallet; b) sensor locations across cardboard layers A–D; c) sensor positions within the cold storage facility; d) sensor positions within the refrigerated container.

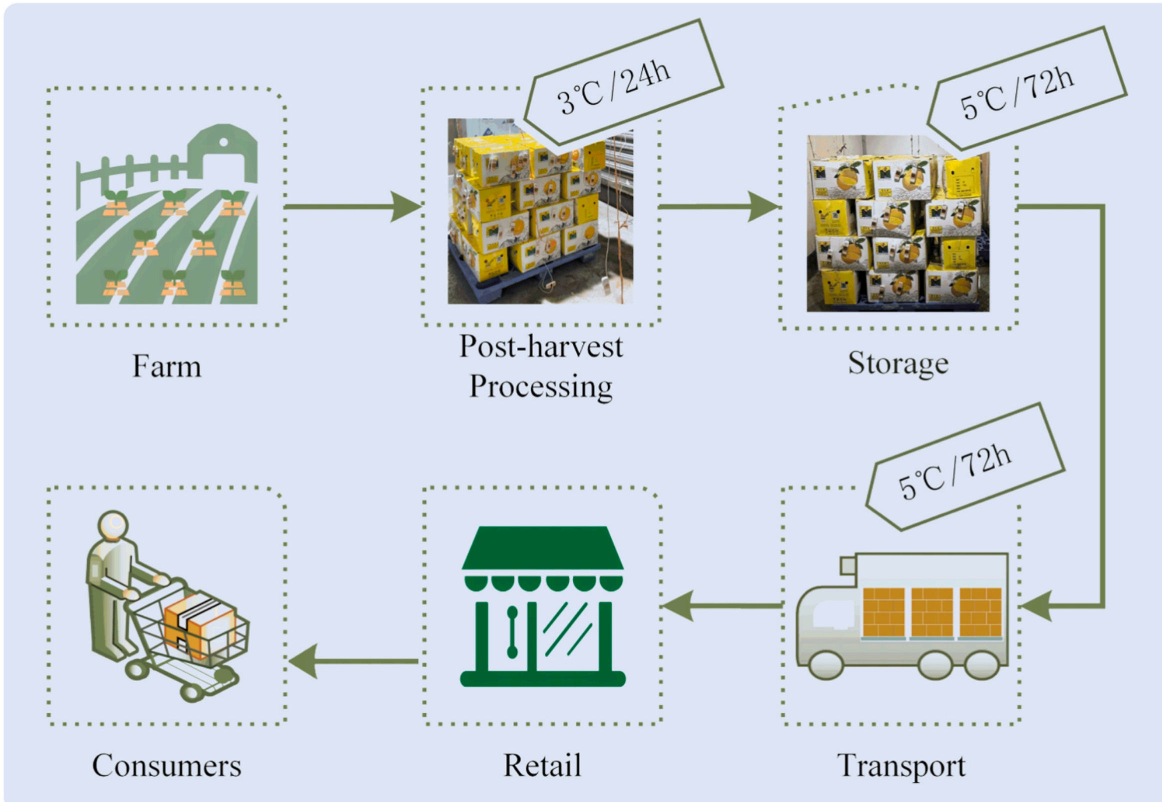

Fig. 5. Supply chain scenarios.

($5.0 \times 3.0 \times 2.8$ m^3) was equipped with an automatic refrigeration unit (Fig. 2a) and fitted with two front exhaust grilles (Ø0.6 m) and two rear return air grilles (Ø0.4 m). Transport was simulated with a standard 20-foot refrigerated container ($5.69 \times 2.13 \times 2.18$ m^3; Fig. 2b) containing a mechanical refrigeration system, a front exhaust grille (0.9×0.2 m^2), and a rear return air grille (0.7×0.15 m^2).

2.1.2. *Navel orange and carton types*

Navel oranges were obtained from an orchard in Chongqing (Southwestern China) and transported under ambient conditions to the cold-chain logistics laboratory at Guangzhou University for postharvest precooling. Two trials were carried out in winter and summer. The test fruits were "Fengyuan" navel oranges with diameters of 45–75 mm and weights of 150–350 g (Fig. 3a). After minimal processing, the fruits were packed in corrugated boxes ($0.4 \times 0.3 \times 0.35$ m^3), each containing two ventilation holes on each side and holding approximately 10 kg of fruit (Fig. 3b). To account for the significant variations in shelf life and spatial temperature reported by Mercier and Uysal (2018) in four-layer pallets, the pallets in this study were arranged in four layers (Fig. 3c). Each high-cube pallet ($1.2 \times 1.0 \times 1.4$ m^3) contained eight boxes per layer, for a total of 32 boxes.

2.1.3. *Placement of temperature sensors*

Fruit skin temperature was monitored using RC-5+ sensors (Shenzhen, China; accuracy ±0.5 °C, 1-min logging interval). Probes were inserted into predetermined positions within the boxes prior to palletization. Each pallet contained 32 boxes arranged in four layers (Fig. 4a), with 16 sensors deployed per layer (Fig. 4b). Sensor positions were encoded following Margeirsson et al. (2012) using a three-character code: the first character indicates the layer (A–D), the second specifies the box location within the layer (1–8), and the third denotes the sensor's position within box (1–2). For example, A81 refers to a sensor placed in a corner box on the bottom layer.

A total of 27 environmental temperature sensors were installed (Fig. 4c and d), with each spatial section (E1–E3) containing nine sensors, following the layout described by Zou et al. (2023). Sensor coding mirrors that of the fruit temperature sensors: the first character, ''E'' indicates environmental temperature; the second digit (1–3) denotes the spatial section; and the third digit (1–9) specifies the sensor's position within the section. For example, E19 denotes the sensor in the lower right corner of section E1, opposite the fan. The same layout was applied to both the cold storage facility and the refrigerated container.

2.1.4. *Supply chain scenarios*

This study conducted experimental simulations to obtain temperature data for food pallets along the FSC, focusing on three stages: (1) postharvest processing (precooling); (2) storage; and (3) transport (Fig. 5). Oranges equipped with temperature sensors were precooled at 3 °C for 24 h, stored at 5 °C for 72 h, and then transferred to a refrigerated container precooled to 5 °C for an additional 72 h.

2.2. *Deep learning method*

2.2.1. *Multi-source data selection and partitioning*

Prior studies have shown that multisource data can improve prediction accuracy, but redundant inputs may increase costs and complexity (Han et al., 2021). Correlation analysis of earlier datasets (Meng et al., 2024; Zou et al., 2025) (Fig. 6) was used to guide feature evaluation. Pre-cooled state (PCS) and door status (DS) were excluded due to high correlation and low relevance ($|r| < 0.3$), and the final feature set included initial food temperature (IFT), internal ambient temperature (IAT), and pallet food temperature (TFP). The dataset was split sequentially, with the first 80 % used for training and the remaining 20 % for testing, in order to preserve temporal order and avoid leakage of future information into the training set (Joseph, 2022).

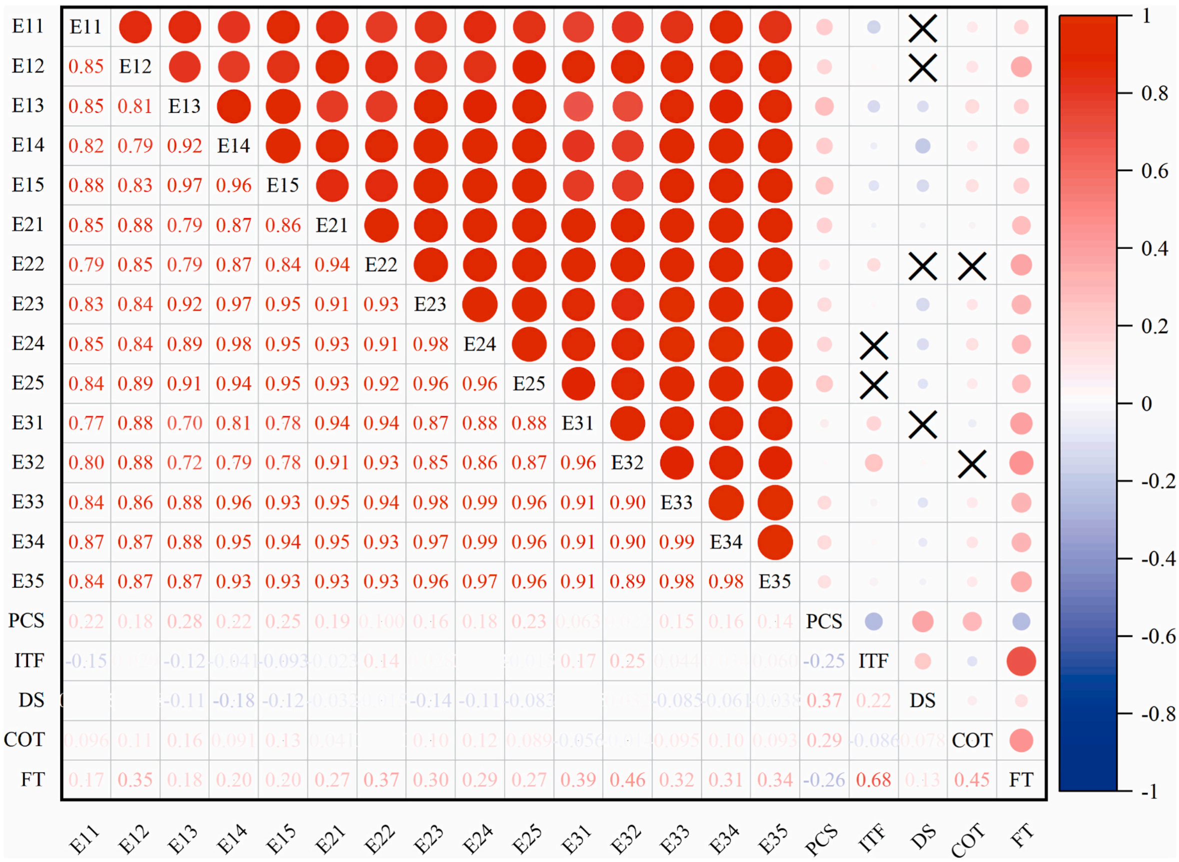

Fig. 6. Spearman's correlation analysis among multisource data (*Note:* E denotes internal ambient temperature. PCS, IFT, DS, COT, and FT represent pre-cooled state, initial food temperature, door status, cumulative open time, and food temperature, respectively).

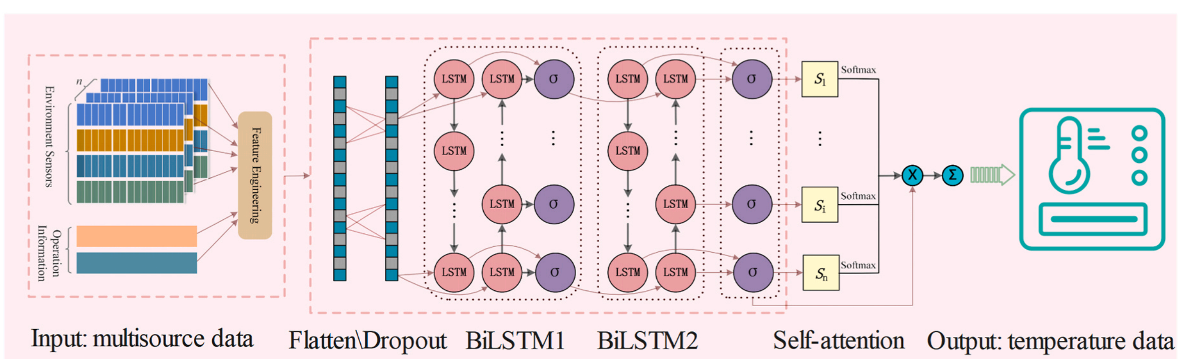

Fig. 7. Structure of the deep neural network for temperature prediction.

Table 1
RMSE (°C) of model predictions under different parameter conditions.

	Hidden size			Batch size				Dropout rate			
Value of parameters	5	10*	15	20	50	100*	150	200	0	0.1*	0.2	0.3
RMSE (°C)	0.18	0.16	0.16	0.11	0.15	0.16	0.18	0.2	0.16	0.16	0.16	0.16

Notes: "*" denotes the optimal parameter value.

2.2.2. *Overview of the proposed method*

Previous studies have employed RNNs, CNNs, and SAEs (Kataria and Singh, 2018; Yuan et al., 2020a, 2020b), with LSTM networks, as a variant of RNN, shown to be particularly effective for capturing sequential dependencies in time-series data (Beck et al., 2024; Shen et al., 2020). On this basis, multisource data in this study were processed using a BiLSTM with an attention mechanism to generate temperature estimates at multiple locations. The framework of the proposed neural network model is shown in Fig. 7.

Incorporating self-attention enabled the model to weigh information across locations in sequential data. Input data were normalized, and a dropout rate of 0.1 was applied to prevent overfitting. Seasonal

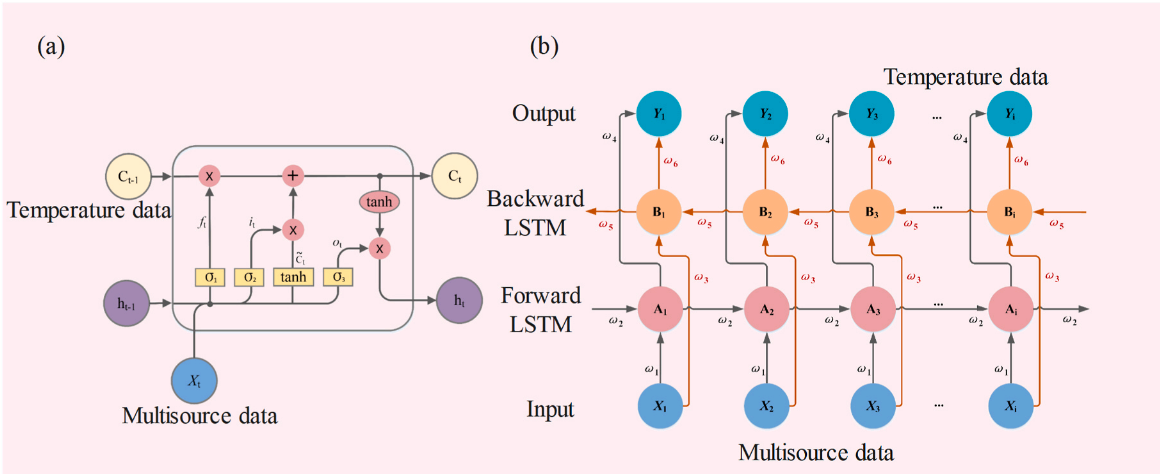

Fig. 8. A module of the BiLSTM neural network (a) LSTM cell; (b) BiLSTM.

experiments were conducted, with the first cycle in each season used for training and the second for validation. Table 1 summarizes the hyper-parameter analysis: hidden size showed little effect on accuracy, so 10 neurons were used to reduce computational demand; reducing batch size slightly increased RMSE, but a size of 100 was adopted to accelerate training; and dropout rate had negligible impact, confirming adequate generalization.

2.2.3. LSTM network structure

The LSTM network consists of a sequence of cells, each with an input, forget, and output gate (Fig. 8a). The input gate controls how new information is added to the cell state, the forget gate determines which information is discarded, and the output gate specifies what is passed to the next layer. This gating mechanism allows the network to retain information over long sequences. The operation of the forget gate f_t can be

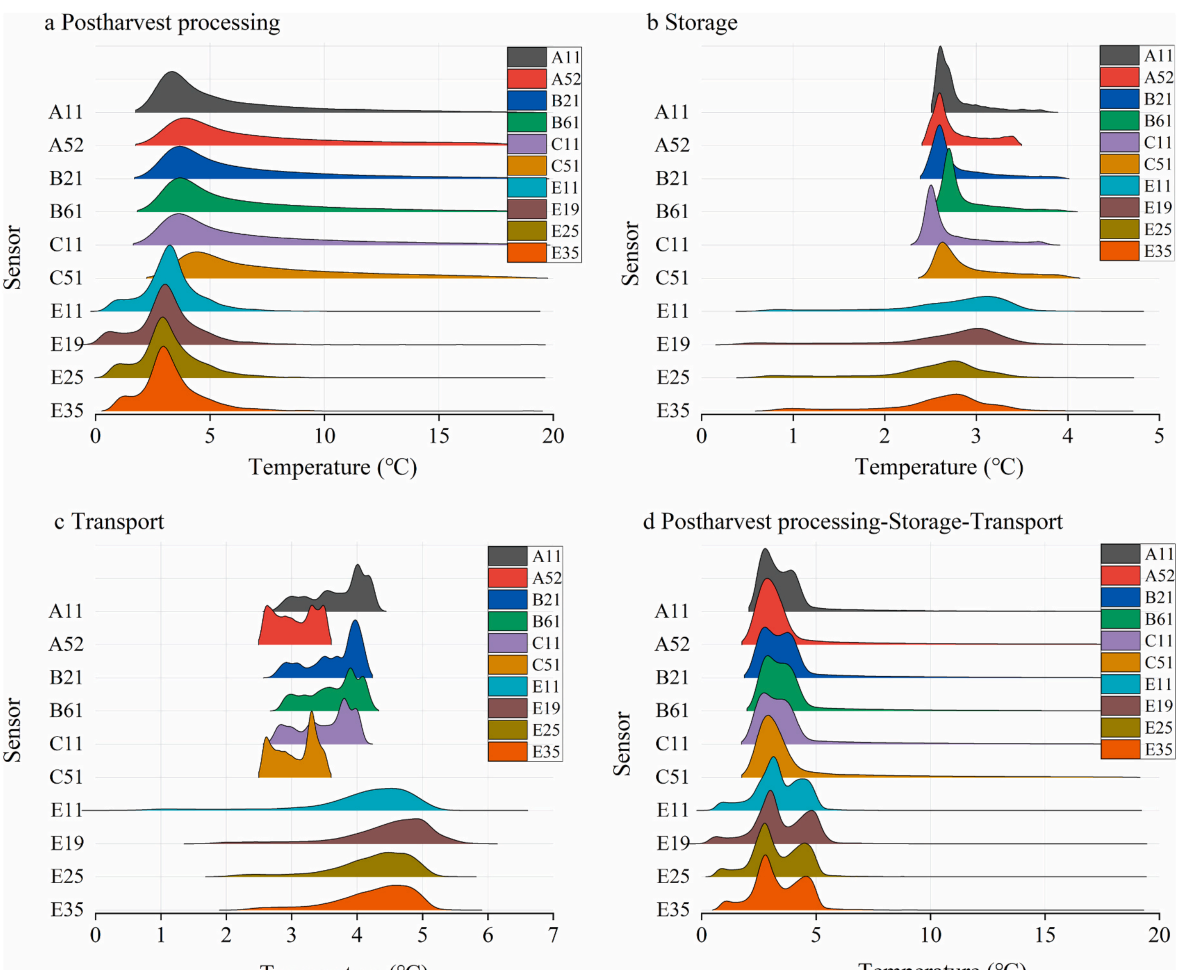

Fig. 9. Temperature along the FSC.

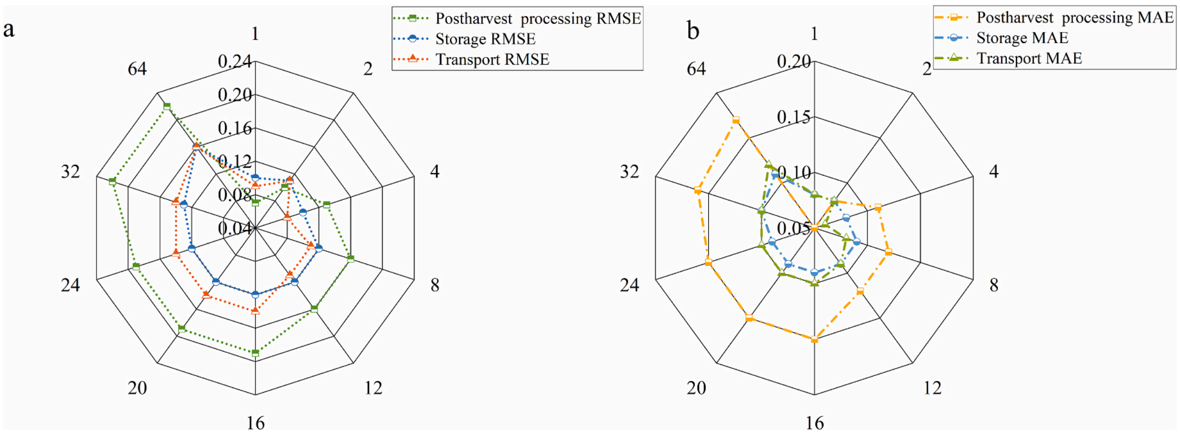

Fig. 10. DD-VSS prediction performance across FSC stages.

expressed as:

$$C_t = f_t \times C_{t-1} + i_t \times \widetilde{C}_t \tag{1}$$

where h_{t-1} is the previous hidden state, x_t is the current input, W_f represents the weight matrix, b_f is the bias term, and σ_1 denotes the sigmoid activation function.

At time step t, the input gate i_t and the candidate vector from the tanh layer jointly update the cell state C_t.

$$i_t = \sigma_2(W_i \cdot [h_{t-1}, x_t] + b_i) \tag{2}$$

$$\widetilde{C}_t = \tanh\left(W_c \cdot [h_{t-1}, x_t] + b_c\right) \tag{3}$$

$$C_t = f_t \times C_{t-1} + i_t \times \widetilde{C}_t \tag{4}$$

In the above formula, W_i, b_i, and W_c, b_c denote the weight matrices and biases of the input gate and the cell state, respectively. The output gate is defined as:

$$o_t = \sigma_3(W_o \cdot [h_{t-1}, x_t] + b_o) \tag{5}$$

$$h_t = o_t \times \tanh(C_t) \tag{6}$$

Where, W_o and b_o are the weight and bias of the output gate.

One-way training may fail to capture temporal dependencies from later to earlier time steps. To address this, a bidirectional LSTM (BiLSTM) model was used (Fig. 8b). The BiLSTM integrates two LSTM layers: one processes the sequence forward (past to present) and the other backward (future to present), thereby combining bidirectional dependencies for improved feature extraction. The hidden state updates of the forward and backward layers and the BiLSTM output are defined in Eqs. (7)–(9).

$$A_i = f_1(\omega_1 x_i + \omega_2 A_{i-1}) \tag{7}$$

$$B_j = f_2(\omega_3 x_i + \omega_5 B_{i+1}) \tag{8}$$

$$Y_i = f_3(\omega_4 A_i + \omega_6 B_i) \tag{9}$$

Where f_1, f_2, and f_3 denote the activation functions of different layers. By integrating information from both directions, the BiLSTM captures temporal dependencies more comprehensively, thereby enhancing data utilization and improving prediction accuracy.

2.3. Model performance evaluation

Two metrics are employed to evaluate the proposed model: root mean square error (RMSE) and mean absolute error (MAE) (Qin et al., 2024), as defined in Eqs. (10) and (11).

$$RMSE = \sqrt{\frac{1}{m}\sum_{i=1}^{m}(T_i - \widehat{T}_i)^2} \tag{10}$$

$$MAE = \frac{1}{m}\sum_{i=1}^{m}|T_i - \widehat{T}_i| \tag{11}$$

where $\hat{T}_i$ denotes the predicted temperature and T_i the actual value. Following industry standards and Hafliðason et al. (2012), an allowable prediction error of 0.5 °C is adopted, which corresponds to a 10 % shelf-life estimation error (Zou et al., 2023).

To further assess the economic performance of virtual sensors, an equivalent replacement rate (ERR) is defined, representing the ratio of virtual to physical sensors under the allowable temperature error of 0.5 °C, as shown in Eq. (12).

$$ERR = Q_v / Q_p \tag{12}$$

where Q_v and Q_p denote the numbers of virtual and physical sensors, respectively. A higher ERR indicates greater economic efficiency, as fewer physical sensors are needed to achieve the same accuracy in temperature monitoring.

3. Results

3.1. Analysis of experimental data results

Along the FSC, the temperatures of individual food items within pallets exhibit heterogeneity (Fig. 9a–eg., A11 vs. A52), consistent with the findings of Nunes et al. (2014) and Shrivastava et al. (2022). Moreover, foods possess high thermal inertia, leading to slower responses to ambient fluctuations (Fig. 9a–c, item C51 vs. ambient E11). This divergence results not only from thermal inertia but also from product-specific characteristics such as initial temperature, respiration heat, thermal conductivity, and packaging. Consequently, ambient air temperature cannot be considered a reliable proxy for actual food temperature in cold chain environments.

3.2. Performance of the DD-VSS

DD-VSS achieved RMSE and MAE values below 0.3 °C in predicting food temperatures across FSC stages, including postharvest processing, storage, and transportation (Fig. 10a & b; Appendix A), remaining within the generally accepted error tolerance of 0.5 °C. Prediction errors decreased from postharvest processing to transportation and storage, reflecting differences in temperature variation ranges and consistent with prior findings that larger variations reduce accuracy. When the

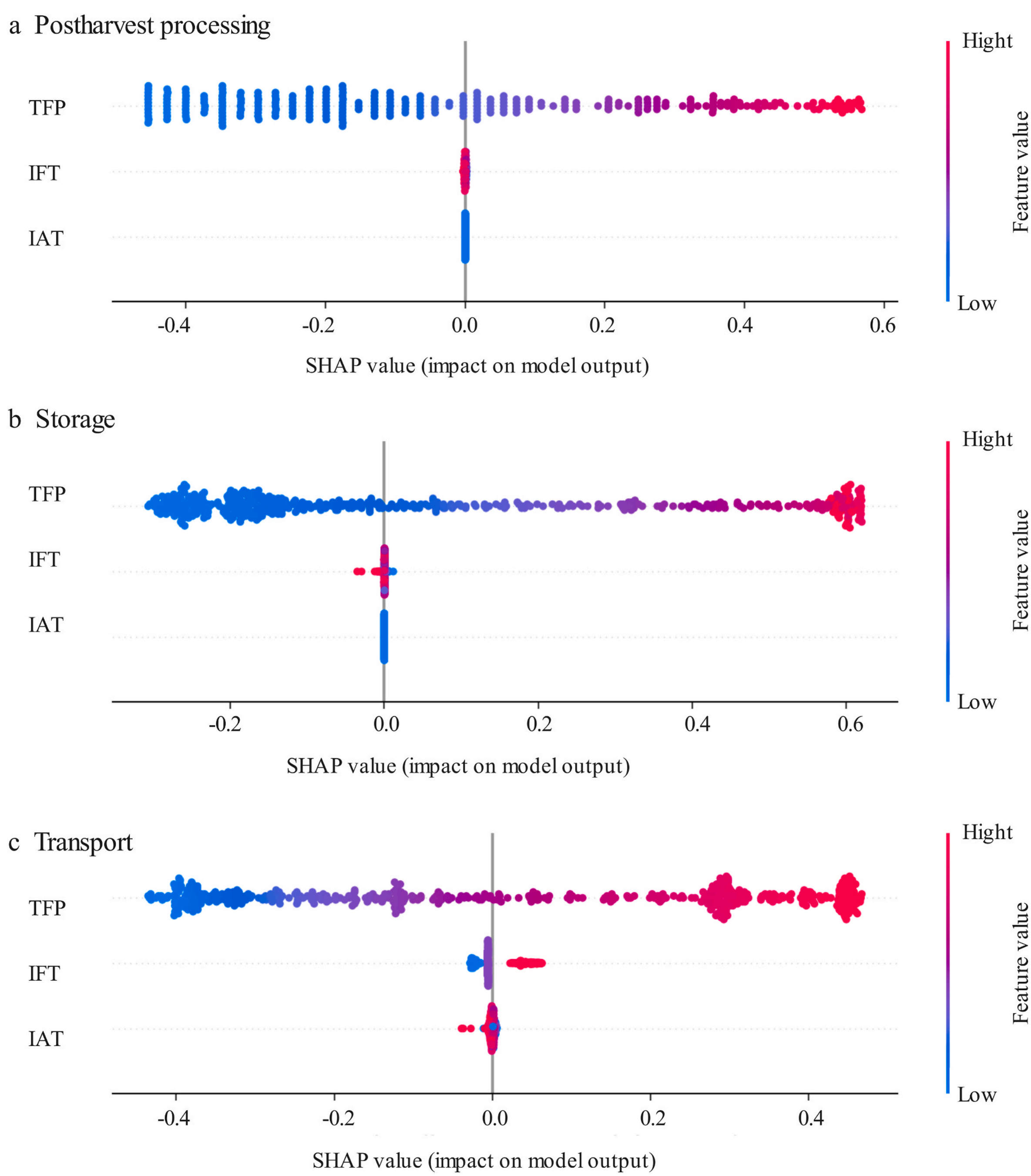

Fig. 11. Influence of multisource features on DD-VSS prediction performance across FSC stages (IFT: initial food temperature; IAT: internal ambient temperature; TFP: pallet food temperature; BS: baseline scenario).

number of virtual sensors was increased while keeping the number of physical sensors fixed (e.g., one ambient and one tray sensor), the impact on accuracy was limited. For instance, in postharvest processing (green line, Fig. 10a), RMSE increased moderately from 0.13 °C (ERR = 2) to 0.22 °C (ERR = 32).

3.3. *Influence of multisource data on prediction accuracy*

To quantify the contribution of each multisource feature to virtual sensor performance, the DD-VSS was evaluated at an ERR of 32 across postharvest processing, storage, and transportation. As shown in Fig. 11, temperature data from pallet sensors exerts the greatest influence on prediction accuracy across all stages.

Pallet-level food temperature measurements showed the highest SHAP values, ranging from −0.4 to 0.6 during postharvest processing, −0.2 to 0.6 during storage, and −0.4 to 0.4 during transportation, highlighting their central role in predictive accuracy. In contrast, internal ambient and initial food temperatures exhibited negligible SHAP values. These findings are consistent with Badia-Melis et al. (2018), who emphasized the importance of pallet-mounted sensors for accurate temperature management along the FSC. At least one pallet-mounted temperature sensor is therefore recommended for effective monitoring.

3.4. *Impact of the sensor location on the performance of DD-VSS*

Sensor placement on the pallet had minimal impact on DD-VSS temperature prediction. Accuracy was evaluated at the center of 32 boxes under different sensor locations. DD-VSS achieved RMSE values of

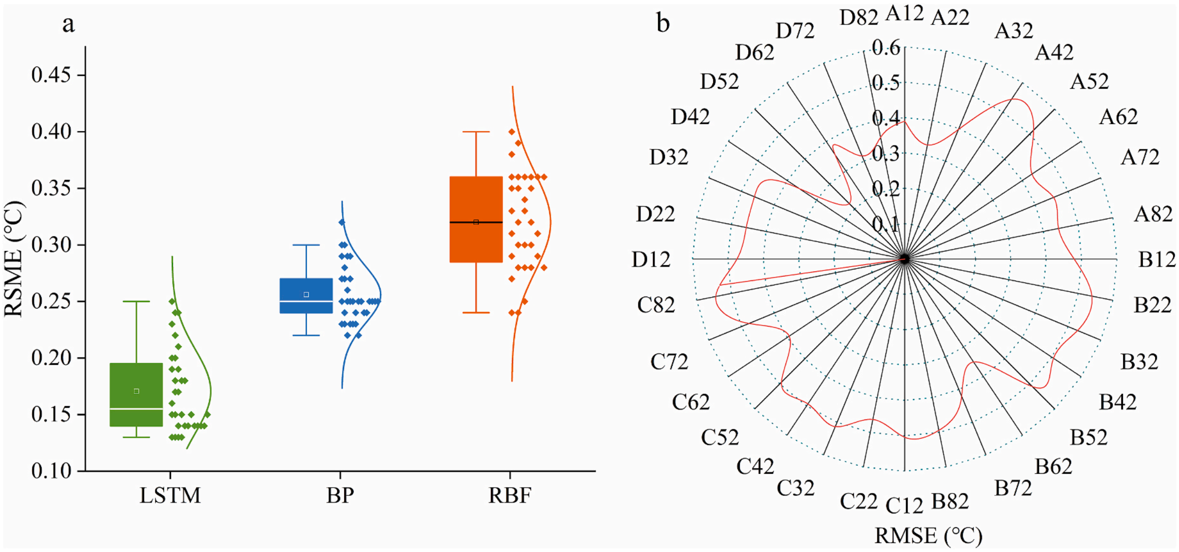

Fig. 12. Comparison of predictive performance at different pallet sensor locations: (a) DD-VSS, (b) ARIMAX.

Table 2
Comparison of the performances of the PB-VSS and DD-VSS.

Model types	Model	Objects	Logistics scenario	NPS	NVS	ERR	RMSE (°C)	Reference
Physics-based	Kriging	Pallets in container	Transportation	16	24	1.5	1.32	Badia-Melis et al. (2016)
	Inverse distance weighing	Pallets in truck	Transportation	8	32	4.0	1.11	Jedermann & Lang (2009)
	Ordinary Kriging	Pallets in truck	Transportation	8	32	4.0	2.20	Jedermann & Lang (2009)
	Liner curve fitting	Pallets in truck	Transportation	8	32	4.0	0.42	Jedermann et al. (2011)
	Cross-attribute Kriging	Pallets in container	Transportation	8	52	6.5	0.76	Palafox-Albarran et al. (2015)
	Fuzzy multiple objective decision-making	Pallets in truck	Transportation	7	27	3.9	1.79	Liu et al. (2014)
Data-driven	ANN*	Pallets in truck	Transportation	8	40	5.0	0.11	Badia-Melis et al. (2016)
	ANN	Pallets in truck	Transportation	4	40	10.0	0.32	Badia-Melis et al. (2016)
	ANN	Pallets in truck	Transportation	3	40	13.3	0.37	Badia-Melis et al. (2016)
	ANN	Pallets in truck	Transportation	1	40	40.0	1.49	Badia-Melis et al. (2016)
	ANN	Pallet	FSC	1	16	16.0	0.95	Loisel et al. (2022)
	ANN	Pallet	FSC	2	16	8.0	0.65	Loisel et al. (2022)
	ANN	Pallets in multi-temperature truck	Delivery	4	40	10.0	0.54	Zou et al. (2023)
	LSTM	Pallets in multi-temperature truck	Delivery	4	40	10.0	0.24	Zou et al. (2023)
	Deep learning	Pallets in truck	Delivery	4	40	10.0	0.33	Zou et al. (2023)
	LSTM + Attention	Pallet	FSC	2	64	32.0	0.22	This paper

Note: ANN, NPS, NVS, and ERR are artificial neural networks, the number of physical sensors, the number of virtual sensors, and the equivalent replacement rate, respectively.

0.13–0.25 °C (avg. 0.17 °C; Fig. 12a), compared with 0.22–0.32 °C (avg. 0.26 °C) for the BP neural network and 0.24–0.40 °C (avg. 0.32 °C) for the radial basis function network. Thus, DD-VSS performance is insensitive to sensor placement, with prediction accuracy more strongly determined by network architecture.

Sensor placement had little effect on DD-VSS but strongly influenced statistical models. With the same dataset (sensor A11, initial food temperature, and environmental temperature), the ARIMAX model yielded RMSE values of 0.10–0.59 °C (variation 0.49 °C; Fig. 12b), whereas DD-VSS errors varied by only 0.15 °C across locations. Thus, DD-VSS maintained robust predictive accuracy regardless of sensor placement, while statistical models were more sensitive and required optimal sensor positioning.

4. Discussion

4.1. Advantages of the DD-VSS method

Although PB-VSS can be used to manage temperatures along the FSC, DD-VSS demonstrates substantially higher accuracy. As shown in Table 2, PB-VSS RMSE ranges from 0.42 °C to 2.20 °C, whereas DD-VSS RMSE ranges from 0.11 °C to 1.49 °C, indicating approximately 50 % improvement in predictive accuracy. For instance, Badia-Melis et al. (2016) reported that Kriging with 16 sensors (bottom layer only) achieved an RMSE of 1.32 °C, while an ANN with 8 sensors reached 0.11 °C. In terms of cost-effectiveness, DD-VSS also outperforms PB-VSS, achieving a maximum ERR of 32 compared with 6.5 for PB-VSS, while maintaining lower prediction errors.

Performance within DD-VSS also varies depending on the neural network architecture. Deep neural networks with multiple hidden layers achieve lower prediction errors than shallow networks, such as BP, reflecting their greater capacity to model complex data patterns. The

Table 3
Comparative DD-VSS and industrial-grade IoT solutions.

Dimension	Metric	DD-VSS	Industrial IoT	Basis/ Source/ Notes
Accuracy	Temperature MAE	±0.3 °C	±0.5 °C	IEC (2024)
	Misclassification	0.80 %	2 %	Zaidan et al. (2023)
	Early warning lead time	6–8 min	2–3 min	Predictive advantage
	Data completeness	99.70 %	94 %	Industrial sensors 3-year failure rate ~6 %
Deployment	Installation time per vehicle	20 min	45–60 min	DD-VSS reuses CAN & cameras; IoT requires wiring/ drilling
	Fleet downtime	0 %	5 %	IoT installation ~0.5 day/ vehicle
	Upgrade/ maintenance	OTA model update (<50 MB)	Sensor/ firmware replacement	OTA allows night-time updates
	Multi-vehicle adaptation	Standardized CAN signals	Custom brackets & wiring	IEC (2024)

incorporation of attention mechanisms further improves performance; in this study, combining deep networks with attention increased ERR and reduced prediction errors relative to results reported by Zou et al. (2023). These results indicate that neural network architecture significantly affects DD-VSS performance and the overall efficiency of temperature monitoring systems.

4.2. Comparative DD-VSS and industrial IoT solutions

The DD-VSS was assessed against industrial-grade cold chain IoT solutions in predictive performance and deployment efficiency. For a fleet of 1000 trailers over three years, with six operations per year and goods valued at $10,000 per trail DD-VSS is estimated to reduce spoilage by 5 % (Zou et al., 2025), yielding annual savings of ~$1.6 million. The system's deployment cost is $2.2 million, with an estimated payback period of around 1.5 years (detailed calculations in Appendix B).

As shown in Table 3, DD-VSS demonstrates higher predictive accuracy than industrial IoT systems (MAE ±0.3 °C vs. ±0.5 °C; misclassification 0.8 % vs. 2 %), faster early warning capability (6–8 min vs. 2–3 min), and greater data completeness (99.7 % vs. 94 %). Deployment is also more efficient and less intrusive, requiring approximately 20 min per trailer without downtime and supporting over-the-air (OTA) updates and multi-vehicle compatibility, compared with 45–60 min, ~0.5 days of downtime, and hardware modifications for conventional systems. While Thermo King emphasizes hardware-based refrigeration and Sensitech focuses on sensor-driven monitoring, DD-VSS leverages virtual sensing to generate high-resolution data from a reduced number of sensors, thereby decreasing system complexity and improving scalability.

4.3. Generalization of DD-VSS model

To evaluate the generalization capability of the DD-VSS model, a field test was conducted with Guangzhou Transportation Group's Cold Chain Delivery Center (Appendix C). The test involved one refrigerated vehicle used for banana distribution over eight days (July 30–August 7, 2025). The truck carried four pallets (24 boxes each), with ventilation gaps left between pallets. A total of 37 temperature sensors (five per pallet) and one door-status sensor were installed.

During operation, the carriage temperature was set to 12 °C, with 10 delivery points per day. Loading–unloading intervals ranged from 35 to 60 min, and doors remained open 6–20 min at each stop. Both precooled and non-precooled states were tested, including two non-precooled days. To simulate non-standard conditions, the refrigeration system experienced 15 h of faults (fan failure, partial return-air blockage, partial supply-air blockage, each lasting 5 h). Door-opening times of 12, 16, and 20 min were also tested under fault conditions.

A total of 16,507 valid records were collected during the experiment. The DD-VSS model yielded RMSE = 0.30 °C and MAE = 0.21 °C between predicted and observed temperatures. As shown in Fig. 13a, the actual and predicted temperature curves for the 20th measurement point were nearly identical, demonstrating close alignment. Extending the comparison to the first 50 samples (Fig. 13b) showed that the model consistently followed observed dynamics, even under delivery conditions with temperature fluctuations of up to ≈10 °C.

4.4. Future applications of the DD-VSS method

Although early implementations of DD-VSS were restricted by data and computational limitations, recent developments in IoT and high-performance computing have enabled the integration of AI and big data analytics in FSC. This integration supports more precise temperature monitoring and control (Chen et al., 2022) and may reduce losses

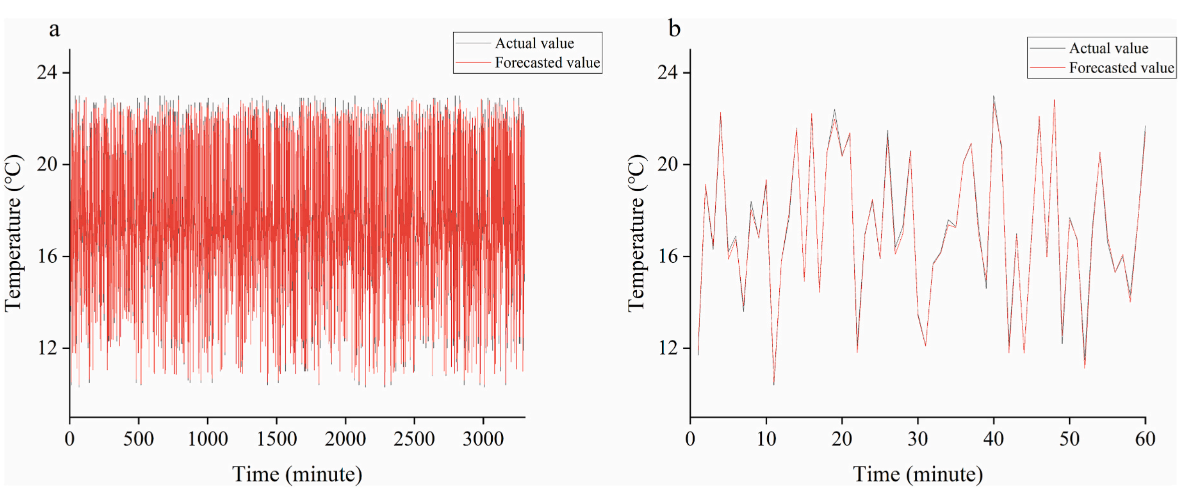

Fig. 13. Model validation.

Table 4
The system's strategies for addressing operational challenges.

Challenge Area	Specific Challenge	DD-VSS Solution	Resulting Benefit
Real-Time Processing	High throughput, low latency	Edge inference + load-balanced clusters	Sub-second response, real-time monitoring
Large-Scale Concurrency	Scalable processing	Horizontal scaling of edge nodes	Linear throughput growth with fleet size
Cloud Cost & Elasticity	Bandwidth and computational expense	Exception-based reporting; cloud handles non-real-time tasks	>95 % reduction in bandwidth/cost, demand-driven resource usage
Centralized Management	OTA updates, configuration, monitoring	Unified cloud management of all edge nodes	Efficient fleet-wide operation and updates
Reliability	Edge deployment stability	N+1 redundancy and automatic failover	Industrial-grade reliability
Deployment Efficiency	Non-intrusive installation, multi-vehicle adaptation	OBD-II/CAN interface; standardized protocols	50 % faster deployment, scalable installation
Remote Operations	Maintenance and monitoring	Containerized edge services with cloud monitoring	Reduced on-site maintenance and operational cost

associated with temperature variability (Varriale et al., 2024; Toorajipour et al., 2021). DD-VSS can reduce reliance on physical sensors, with estimates indicating that a system implementing equivalent replacement rate (ERR = 8, 16, 32) would require 1.71 billion, 850 million, and 430 million sensors, respectively, compared with 13.7 billion for full coverage of fresh foods, including fruits and vegetables (Appendix D). This suggests potential economic benefits and broader applicability along the FSC.

Nonetheless, challenges remain. Standardized guidelines for DD-VSS development are limited, large-scale deployment cases are sparse, and technology maturity and generalization performance are not fully established. Integrating operational enterprise data could improve model robustness (Loisel et al., 2022). Large-scale deployment may also require high-precision sensors, low-latency networks, and significant computing resources, incurring both initial and maintenance costs. A careful balance between economic, technical, and operational factors is necessary to ensure practical feasibility. Strategies for addressing these considerations are summarized in Table 4 (Appendix E).

To address these challenges, the DD-VSS in this study adopts a hybrid edge–cloud architecture for large-scale cold-chain monitoring. Edge nodes perform real-time inference with optimized BiLSTM + Attention models, achieving sub-second latency and high throughput, while only transmitting exception data to the cloud to reduce bandwidth demand. System reliability is further enhanced through N+1 redundancy, containerized deployment, and standardized non-intrusive vehicle integration, facilitating efficient fleet-wide deployment. This architecture balances latency, scalability, cost, and operational reliability, offering a practical solution for data-driven monitoring.

5. Conclusion

The objective of this study is to develop a DD-VSS capable of achieving precise temperature management for perishable foods along the FSC using a minimal number of physical sensors. This approach integrates IoT, big data, and neural network technologies to enhance food safety and reduce waste. The main conclusions of this work are as follows:

(1) High precision with minimal sensors: DD-VSS can achieve accurate predictions of pallet-level temperature distributions (<0.3 °C) using a single sensor per pallet, and similar predictive performance is generally observed across different perishable food types and scenarios, indicating its potential generalizability.
(2) Flexibility of sensor placement in DD-VSS: The prediction accuracy shows limited sensitivity to the location of physical sensors within a pallet, suggesting that reasonable variations in sensor placement do not substantially affect performance.
(3) Increasing marginal returns of DD-VSS: With a fixed number of physical sensors, adding additional virtual sensors results in only a slight reduction in prediction accuracy. Compared with PB-VSS, DD-VSS generally achieves similar prediction performance with fewer physical sensors, indicating improved sensor efficiency.

This work provides a theoretical foundation for applying DD-VSS to monitor the temperature of perishable foods. Practical implementation remains constrained by factors such as economic conditions and information technology infrastructure. Many existing virtual sensor solutions are currently limited to experimental or pilot settings. Future research should focus on bridging the gap between laboratory studies and real-world commercial deployment to support wider adoption.

CRediT authorship contribution statement

Fenghua Duan: Methodology, Funding acquisition, Conceptualization. **Xiangchao Meng:** Writing – review & editing, Writing – original draft, Validation. **Wentao Wu:** Writing – review & editing, Validation. **Yifeng Zou:** Software, Data curation. **Xiangpeng Zeng:** Writing – review & editing.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jspr.2025.102844.

Data availability

The datasets during the current study are available from the corresponding author upon reasonable request.

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