

Physics-Informed Sequential Learning with KAN-Mamba for Quality Prediction in Agricultural Cold-Chain Data

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Abstract. Fresh-cut vegetables are easily damaged by enzymatic browning after cutting because cell compartmentalisation is disrupted, oxygen diffusion accelerates, and moisture migration changes at the exposed tissue surface. Develop a physics-informed KAN-Mamba model for browning prediction in fresh-cut lettuce, potato, lotus root and cucumber under cold-storage conditions in this study. The model uses Kolmogorov-Arnold network layers for nonlinear multimodal feature mixing, selective Mamba state-space blocks for long-term storage memory, and a soft reaction-consistency constraint based on temperature-sensitive oxidation and browning-rate monotonicity. The input features are RGB colour indices, hyperspectral band ratios, headspace oxygen, relative humidity, storage temperature, vegetable identity and elapsed storage time. In a 72-hour experiment with 1,920 time-stamped records, the proposed model achieved an RMSE of 3.18, an MAE of 2.41, a freshness-grade accuracy of 93.6%, and a high-browning warning recall of 91.7%, and outperformed the conventional machine-learning and sequence-model baselines.

Keywords: *Fresh-Cut Vegetables, Enzymatic Browning, Physics-Informed Learning, KAN-Mamba, Quality Prediction*

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Introduction

Fresh-cut vegetables have begun to be treated as refrigerated convenience foods to reduce the preparation time at home and support centralized processing by restaurants, institutions and retail meal kits. They have a relatively low commercial value because the quality decreases significantly after peeling, slicing, shredding or trimming. Tissue damage exposes the phenolic substrate to oxidative enzymes, releases intracellular water, and increases the contact area between plant tissue and oxygen, thus causing browning; it is one of the earliest and most prominent quality defects [1]. Changes in color are also noticeable to consumers at an earlier stage of microbial spoilage; thus, the economic damage may have occurred before other severe safety indicators appeared [2]. Currently, the quality-control process is a fixed storage-life rule that conducts periodic sampling and manual color inspection; however, in actual operation, different cultivars, maturity, cutting geometry, washing conditions and package permeability lead to varied browning paths [3]. Computer vision has enhanced the objectivity of color measurement, but color descriptors alone are not stable when illumination, surface moisture and tissue translucency change during chilled storage [4]. Spectral sensing has provided more detailed information on pigment, water and phenolic-related absorption, but the connection between spectral signals and browning progression is still non-linear and time-dependent [5]. Cold-chain monitoring has shown that a short-term temperature increase will still harm the quality of the product [6].

Prediction of browning is thus a dynamic modelling problem rather than a simple regression problem on a single image or spectrum. At any time, the browning index is affected by previous oxygen exposure, enzyme activity, substrate availability, moisture transfer and package atmosphere; thus, the model should be able to reflect both local feature interactions and long-term storage memory. Traditional kinetic models have interpretable

parameters for enzyme-catalyzed oxidation but are not suitable for fitting mixed-vegetable categories and heterogeneous processing histories [7]. Classical machine learning can map handcrafted features to quality scores, but it often ignores temporal causality and may be less accurate when the test batch differs from the training batch [8]. Recurrent Neural Networks are used to improve sequence modelling, but long-term memory storage can become difficult to regulate via hidden states [9]. Transformers can capture the long-term dependencies in time, but they often have a quadratic complexity of attention and require a large amount of data for labelled batches [10]. Recently, state-space sequence models have offered a more efficient route for long-term time-series learning, especially in the case of sensor streams with large storage intervals [11]. At the same time, physics-informed learning has also shown that soft constraints can enhance extrapolation in cases of limited labelled observations or altered boundary conditions [12].

This paper studies a KAN-Mamba model based on physical knowledge for predicting browning in freshly cut vegetables and presents three engineering contributions. First, the KAN component is used to learn a smooth nonlinear mapping of the visual, spectral, gas and environmental features. Second, a Mamba state space block is used to simulate long-term memory storage at a lower cost for sequence processing compared with attention-based models. Third, a soft dynamic consistency constraint has been added to prevent physically unreasonable browning rate behavior at different temperatures and oxygen concentrations.

The rest of this paper is organized as follows. Section 2: Browning Mechanisms, Sensing-based Quality Assessment and Sequential Learning Methods for Fresh-cut Vegetable Prediction. Section 3 introduces the proposed physics-informed KAN-Mamba framework and presents the construction of features, model architecture and learning objective with moderate-length mathematical expressions. Section 4 presents the experimental data set, evaluation plan, ablation experiments, robustness analysis and engineering interpretation through quantitative visualization. Section 5 is the conclusion of this paper, and it will briefly introduce the main results and limitations.

Related Work

Browning Mechanisms and Quality Sensing

The reason for enzymatic browning in freshly cut vegetables is that phenolic compounds in the cell wall have been damaged and then oxidized. Cui et al. [13] identified polyphenol oxidase as a key enzymatic target in fresh-cut produce browning, while cutting increases the exposed surface area and alters the local water-activity. Because temperature, oxygen partial pressure, pH, tissue injury and substrate concentration all affect the speed of browning simultaneously, this process cannot be described by a single parameter [14]. Washing and anti-browning can reduce color changes; however, the degree varies among different vegetables, and the link between instrument-measured color and perceived freshness may be broken [15]. Image analysis has been used to quantify browning by means of L^* , a^* , b^* , hue angle, chroma and other browning index indicators, but camera-based measurements need to be normalized when the surface gloss or liquid residue is different [16]. Hyperspectral and multi-spectral data are also sensitive to changes in biochemistry and structure, and different bands respond differently to pigments, water absorption, and tissue oxidation [17]. The problem in industrial application is how to combine all these signals into a predictor that can remain stable when the batch, cut-off form and storage path change [18].

Sequential and Physics-Guided Learning

Sequential learning has been used for food quality prediction because the state of the product changes during storage and is not observed independently at each sampling time. Recurrent networks have been applied to time-dependent freshness estimation, but they are relatively sensitive to long-term storage and irregular sensor sampling [19]. Temporal Convolutional Networks improve parallel training and local pattern extraction, but the receptive field needs to be carefully designed when short excursions have delayed effects [20]. Transformer-based models can represent long-range dependencies through attention, but the computational cost and need for large labeled datasets may limit their use in small industrial trials [21]. Recently, state-space models have gained attention because they can efficiently encode long sequences and maintain a structured temporal update; thus, they are suitable for cold-chain and storage-monitoring data [22]. Physics-guided neural learning adds another layer of reliability by embedding conservation laws, monotonic trends or simplified kinetic relationships

in the loss function to improve generalization when the deployment conditions differ from the training set [23]. Based on the above studies, a model for fresh-cut vegetable browning should be able to learn nonlinear sensor interactions, efficiently track storage memory, adhere to general physical laws, and avoid excessive rigidity in processing variations.

Proposed Methodology

Problem Formulation and Feature Construction

The prediction problem is to forecast a batch of fresh-cut vegetables stored in a cold chain. At each sampling time, the observation vector contains RGB color descriptors, hyperspectral band ratios, headspace oxygen, relative humidity, storage temperature, elapsed storage time and a categorical vegetable identifier. The goal is the browning index of the calibrated image color and expert-confirmed quality labels. Figure 1 is the whole sensing and modelling workflow, which includes sample preparation, multimodal acquisition, feature normalization, physics-informed sequence learning and decision output for shelf-life warning.

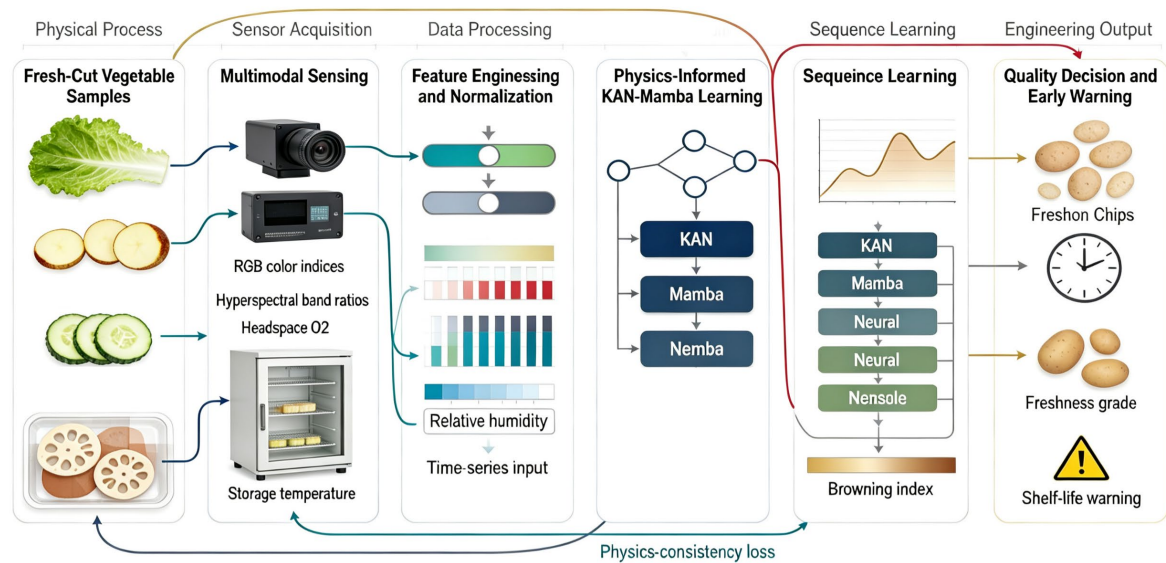


Figure 1. Overall workflow of physics-informed browning prediction for fresh-cut vegetables.

Color features include CIE L^* , a^* , and b^* values, chroma, hue angle, color difference from the initial state, and the conventional browning index. Select spectral features that are visible and near-infrared band ratios related to tissue darkening, surface water and pigment changes. Environmental features are aligned to the same sampling interval and interpolated only within the recorded storage window. To avoid leakage, all normalization parameters are derived from the training set of each cross-validation fold.

Feature construction also shows some practical limitations of fresh-cut production. RGB images are relatively simple to obtain, and they can be taken at the conveyor belt or inside the refrigerated cabinet; however, there is a problem of condensation, surface gloss and local shadows. Spectral Ratios are more stable for biochemical alterations, but they are relatively expensive and may be less frequently observed in daily observations. Gas and humidity sensors provide slow-changing contextual information to explain why the two visually similar samples diverged later. For this reason, the input sequence is designed to tolerate missing channels by masking and time-stamp encoding. When a sensor value is unavailable at a particular time, the model will receive a binary availability flag instead of a hidden imputed value. The absence of oxygen or humidity data generally indicates an operational fault, and in itself, this absence can be regarded as information about process reliability.

The target variable is continuous browning index, and the auxiliary freshness grade is derived from calibrated thresholds agreed upon by visual inspection and instrumental color measurement. A continuous target will maintain small changes over time, and a grade target will have three plant-level decision categories: acceptable, marginal, and unacceptable. The two forms are used to prevent information loss in pure classification and reduce

the ambiguity of pure regression near the action threshold. In training, the 'vegetable' category is not considered a nuisance label but rather a conditioning factor; tissue structure and phenolic composition affect the slope of browning progression. Therefore, the model has learned the general temporal rules and applied them to all categories.

Physics-Informed KAN-Mamba Architecture

The model contains three modules. The first is a KAN feature mixer that introduces nonlinear interactions through learnable univariate spline functions at the network edges. The second is a stack of selective Mamba blocks that propagates storage memory through input-dependent state transitions. The third is a prediction head those outputs both continuous browning index and categorical freshness grade. Figure 2 shows the internal structure of KAN feature expansion, selective state-space recurrence, physics-consistency supervision, and dual-task output.

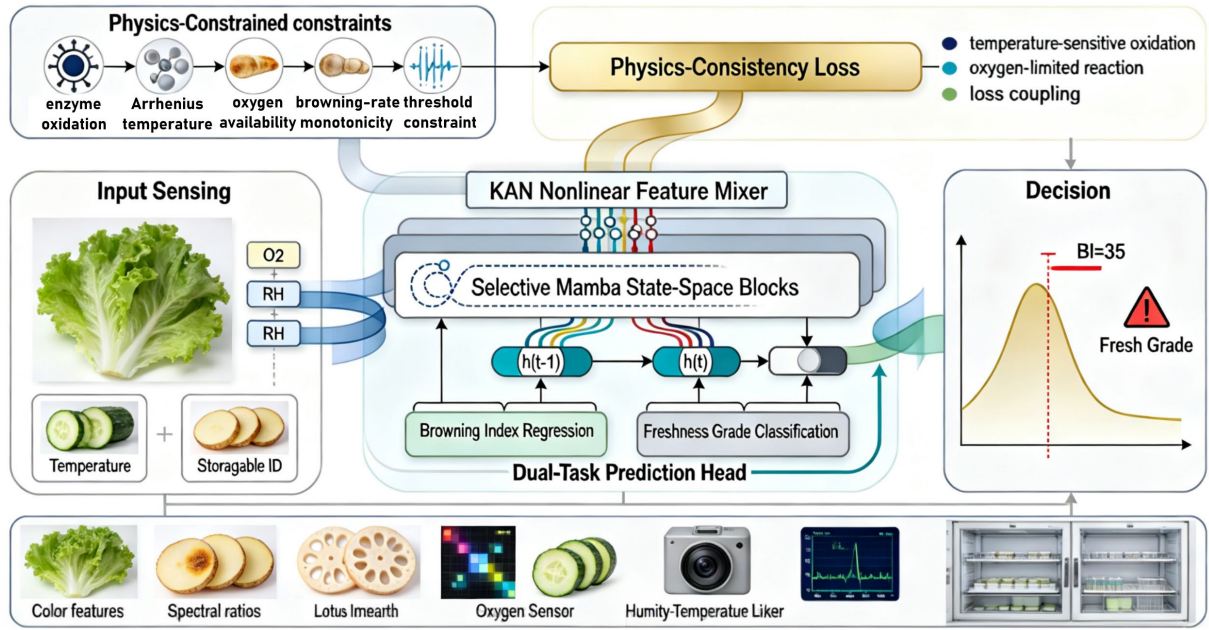


Figure 2. Architecture of the proposed physics-informed KAN-Mamba model.

KAN is added before the sequence backbone because the raw observations at each time step have different physical meanings and measurement scales. A typical dense projection can learn interactions, but these interactions are often lost in the high-dimensional weights. Spline-edge functions are relatively smooth representations of marginal non-linearities, and thus are suitable for cases where the model needs to learn that temperature has little impact during the early storage stage but a significant effect after oxygen and tissue injury accumulate. The Mamba backbone then receives a compressed representation that already contains the nonlinear relationships among sensors. Selective State Updates can be used to focus on abrupt temperature fluctuations, oxygen-depleted zones and other spectral variations by applying different memory rules at different times.

The KAN transformation for the normalized input vector x_t is written as

$$z_t = \sum_{q=1}^Q \Phi_q \left(\sum_{p=1}^P \phi_{q,p}(x_{t,p}) \right) \quad \text{Eq.(1)}$$

where $\phi_{q,p}(\cdot)$ denotes a learnable spline edge function, Q is the number of outer functions, and z_t is the nonlinear mixed representation passed to the sequence module. The selective state-space update is expressed as

$$h_t = A_t h_{t-1} + B_t z_t, y_t = C_t h_t \quad \text{Eq.(2)}$$

where h_t is the latent storage state, A_t and B_t are input-conditioned transition operators, C_t maps the state to the output space, and y_t is the predicted browning index. Temperature sensitivity is introduced through a soft kinetic prior rather than a fixed reaction model:

$$r_t = k_0 \exp\left(-\frac{E_a}{RT_k}\right) g_t \quad \text{Eq.(3)}$$

where the browning-rate surrogate, apparent activation parameter, gas constant, absolute temperature, and bounded oxygen-availability factor define the direction of the soft kinetic prior.

The physical term does not need to be a complete biochemical pathway. Fresh-cut vegetables contain various phenolic substrates and enzymes, and the reaction environment changes after washing, package permeability and tissue moisture. The measurements needed for a model of a rigid mechanism would not be practical in most industrial settings. The soft prior employed here only directs the sign and relative size of browning-rate response under temperature and oxygen changes. This Design allows for exceptions when the observed sensor sequence indicates category-specific behavior, but it does not support predictions that suggest browning recovery or temperature-insensitive deterioration under otherwise similar conditions. Such a compromise is suitable for engineering predictions, and the model needs to be deployable with ordinary sensors.

Training Strategy and Evaluation Protocol

Divide the dataset by production batch rather than by individual images to prevent overestimating the generalization ability. Training uses AdamW with cosine learning-rate decay, early stopping on validation RMSE, and gradient clipping for stable sequence learning. Vegetable identity is represented as a low-dimensional category vector, and storage temperature and gas measurements are continuous variables. Although the model has been trained to predict all time steps, during the evaluation stage, more weight is given to the 24h, 48h and 72h horizons because these periods are operationally relevant to chilled distribution.

Evaluation includes regression accuracy, freshness-grade classification, probability calibration, robustness to sensor noise, and extrapolation under temperature excursions. The baselines are Partial Least Squares Regression, Random Forest, LSTM, Temporal Convolutional Network, Transformer Encoder, KAN without Mamba, and KAN-Mamba without physics regularization. The same batch-level folds are used for all models, and the tests examine whether the physics-guided constraint improves behavior under higher storage temperatures and low-oxygen packaging conditions not fully represented in the training sequences.

Hyperparameters are selected using validation batches instead of random image splits. The number of KAN spline knots, Mamba block depth, hidden dimension and physics-loss coefficient are all set to moderate values to prevent overfitting given the relatively small number of production batches. The final model is a shallow KAN mixer, three selective state-space blocks, dropout in the prediction head, and a physics coefficient that is increased gradually after the first training epoch. This warm-up schedule avoids letting the physical prior overshadow what the model has learned about the mapping between sensor observations and browning status. All reported indicators are averages of the five batch-level folds, and the same folds are applied to all baselines.

Experimental Data and Analysis

Dataset Characteristics and Baseline Comparison

Instrumental color, package atmosphere and spectral indicators are frequently used together to monitor fresh-cut products because browning cannot be described by a single visible descriptor under varying storage conditions [24]. A total of 1,920 time-stamped records from the four fresh-cut vegetable categories in the experiment were used. There were 12 independent processing batches per category, and these batches were kept at 4 °C, 8 °C and 12 °C in a monitored fluctuation of humidity and oxygen. The browning index ranged from 6.8 to 58.4 across all observations. The storage curves in Figure 3(a) show that potato and lotus root darkened faster than lettuce and cucumber, with 72 h mean browning-index values of 47.6, 43.2, 31.9, and 24.7, respectively. The package-atmosphere trend in Figure 3(b) shows that oxygen decreased by 5.4-8.1 percentage points in sealed packages, while the spectral oxidation-ratio curve in Figure 3(c) increased before visible color

exceeded the rejection threshold. The terminal distribution in Figure 3(d) indicates that the interquartile range widened most strongly at 12 deg C, especially for potato slices.

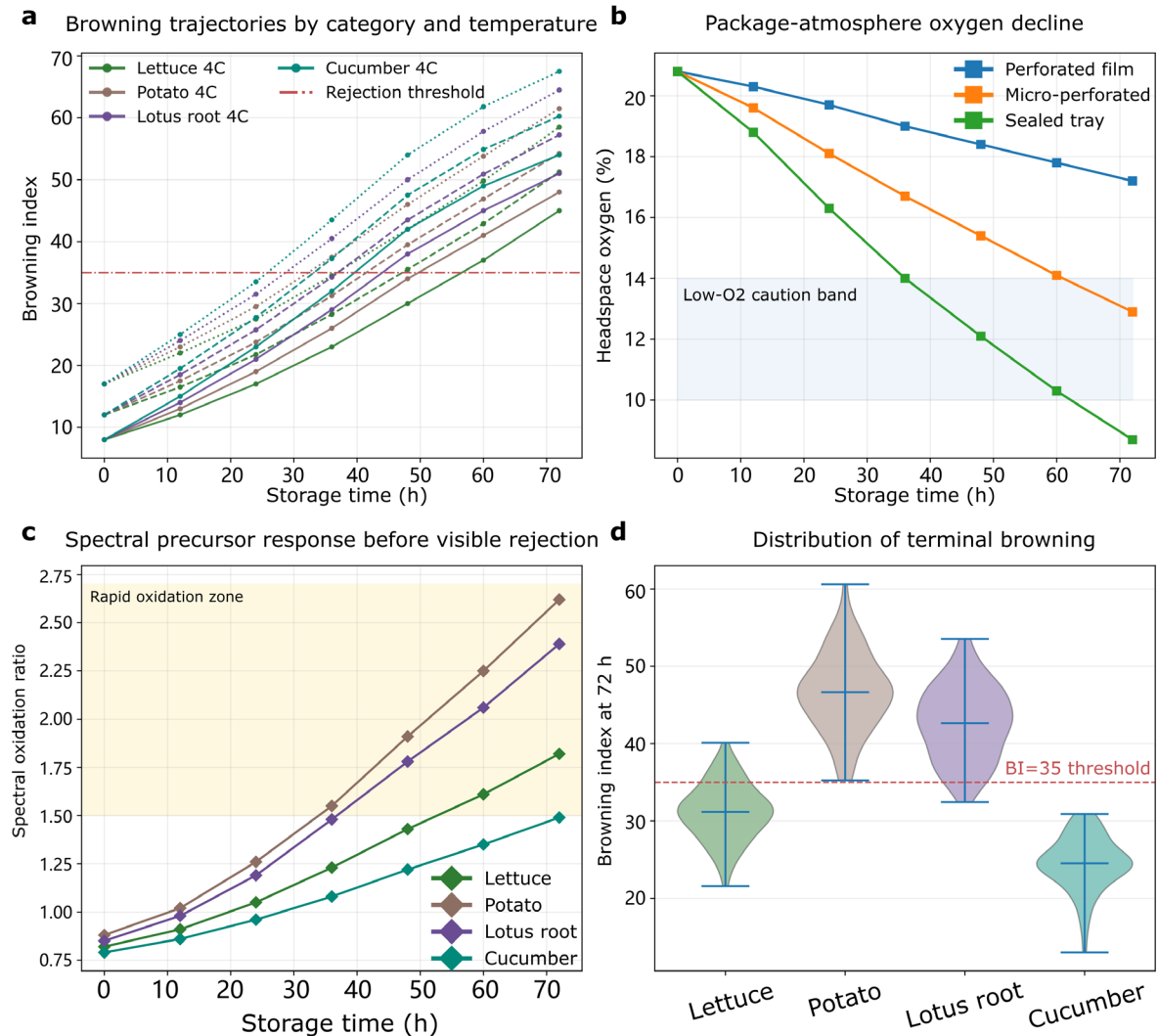


Figure 3. Dataset distributions and storage trajectories: (a) browning-index trajectories by vegetable and temperature; (b) oxygen decline across package conditions; (c) spectral oxidation-ratio evolution; (d) browning-index distribution at 72 h.

Baseline comparison was conducted with the same batch-level split, and batch-level validation is more suitable than random image splitting when the storage history is shared within a production lot [25]. Partial least squares regression had an RMSE of 6.72 because the linear components could not represent the coupling among temperature, spectral variation, and elapsed time. Random Forest reduced RMSE to 5.86 but had unstable long-horizon extrapolation. LSTM, temporal convolution, and transformer baselines obtained RMSE values of 4.61, 4.38, and 4.12, respectively, with freshness-grade accuracies between 86.9% and 89.4%. The error bars and paired metrics in Figure 4(a) show that the proposed physics-informed KAN-Mamba reduced RMSE to 3.18 and MAE to 2.41, while the accuracy line increased to 93.6%. The calibration curve in Figure 4(b) shows that expected calibration error decreased from 0.071 for the non-physical KAN-Mamba to 0.039 for the proposed model.

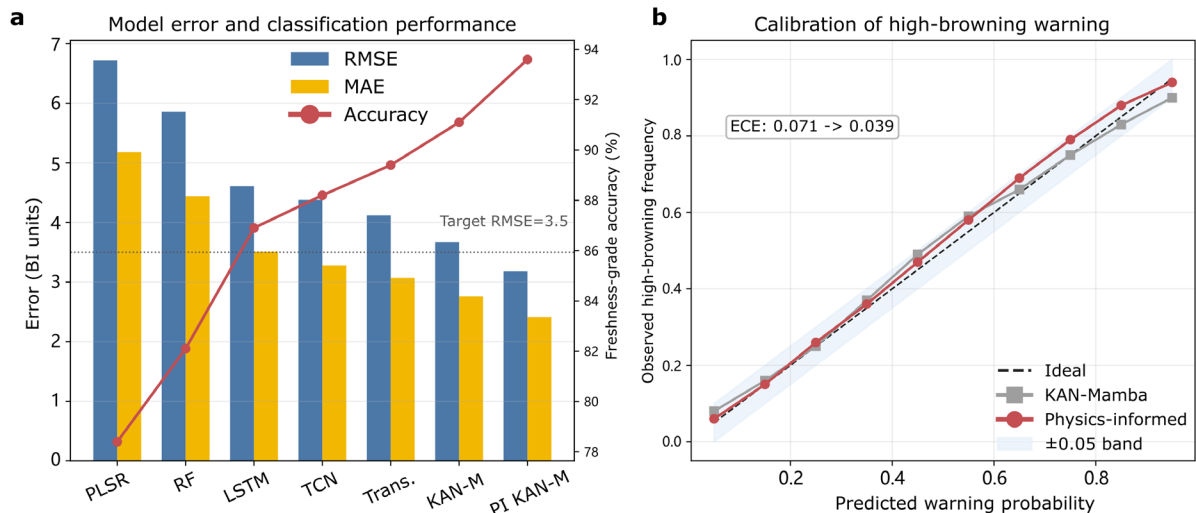


Figure 4. Baseline comparison and calibration: (a) RMSE, MAE, and freshness-grade accuracy across models; (b) predicted probability calibration and high-browning warning reliability.

Near the operating rejection boundary, a small prediction error will result in a change of the accept/reject decision. Calibration and high-risk recall are therefore more informative than the average error alone for a quality-warning system [26]. At a browning-index threshold of 35, the proposed method had a warning precision of 90.5% and a recall of 91.7%; the non-physical KAN-Mamba had reached 87.2% and 84.8%, respectively. The Transformer baseline had more false negatives at 12 °C because it gave more weight to recent color observations and paid less attention to the earlier oxygen decline. The model showed a decrease in hidden quality before visible browning.

The initial results also show the deficiencies of the model families. Linear regression and partial least squares produced smooth predictions but compressed the upper browning range, which is risky because severe browning is precisely the state that needs to be reliably detected. Random Forest found non-linear thresholds, but its predictions were irregular at the split point of a spectral ratio, and thus noisy shelf-life estimates resulted. LSTM performed well in the first 36 hours, but accumulated bias at 60 hours and 72 hours, especially when the early sequence had only a mild color change. The Transformer encoder handled long sequences better, but it had more parameters and the confidence intervals for the small vegetable-specific subset were wider. KAN-Mamba without physics had the best purely data-driven performance, but its residuals were skewed at high temperatures. Residual inspection also showed that most of the baseline errors were not evenly distributed in the browning range. In cases where the browning index exceeds 38, an underestimation phenomenon occurs, while the main reason for overestimation is the slightly discolored cucumbers with bright, moist surfaces. The shape of the asymmetric error affects operations by creating higher-quality risk near the rejection boundary through false acceptances.

Ablation, Robustness, and Physical Consistency

Ablation analysis was performed to separate the contribution of the architecture from that of the physical regulariser, as is common when a hybrid neural model claims both representation learning and mechanism guidance [27]. Removing KAN and replacing it with a linear projection increased the RMSE from 3.18 to 4.05 because the spectral and gas features had category-specific nonlinearities. Removing the Mamba block and using a multilayer perceptron increased RMSE to 4.54 and made 72 h predictions less stable. Removing the physics loss raised RMSE to 3.67 and increased the rate of physically implausible negative browning increments from 1.6% to 7.9%. The component-error bars in Figure 5(a) isolate these changes, Figure 5(b) shows that the 72 h MAE increased most sharply when sequence memory was removed, Figure 5(c) shows that the full model had the narrowest residual-density curve, and Figure 5(d) shows stronger temperature-oxygen contribution for potato and lotus root than for cucumber.

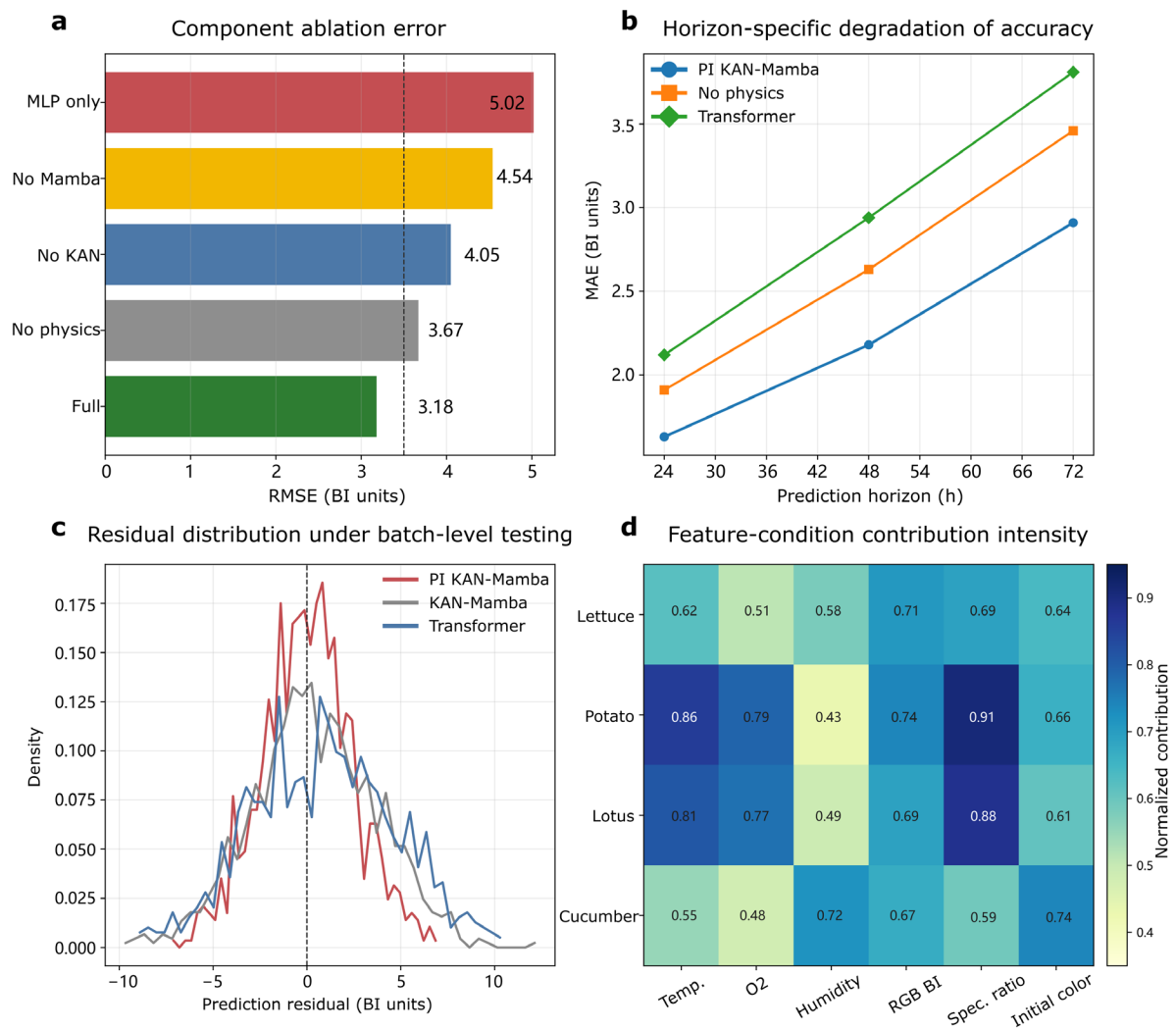


Figure 5. Ablation and feature contribution: (a) component ablation errors; (b) horizon-specific MAE; (c) residual-density comparison; (d) feature-condition contribution heat map.

Robustness is measured by adding sensor noise, masking some sensor channels and testing temperature-excursion sequences. Fresh-cut vegetable plants are not typically in ideal laboratory sensing conditions; camera lenses may accumulate condensation when moving from a cold to a warm room, and headspace sensors can drift after repeated package punctures [28]. Under 5% Gaussian noise in the spectral ratios, the proposed model had an RMSE of only 0.24 and thus outperformed the Transformer (0.51) and LSTM (0.46). Excluding oxygen measurement errors, the RMSE was 3.74, and the model still outperformed the full-input LSTM baseline because the physics-guided constraint promoted a stable evolution of the browning rate.

Temperature-excursion analysis considered a two-hour rise from 4°C to 14°C at 24 hours, as even a short cold-chain deviation can affect the final quality [29]. After 72 hours, the model increased by 9.6 points in the browning index, and the actual value was about 10.1. The non-physical model predicted only a 7.2-point increase and thus underestimated the browning acceleration caused by the temperature disturbance.

Assess the plausibility and consistency of the predicted browning-rate response with the temperature-oxygen gradient physically. Physics-informed learning uses soft constraints to shape the acceptable response surface without needing full mechanistic equations for all samples [30]. As shown in Figure 6, the predicted rate increases continuously with temperature and oxygen supply, and it is bounded under low-oxygen conditions.

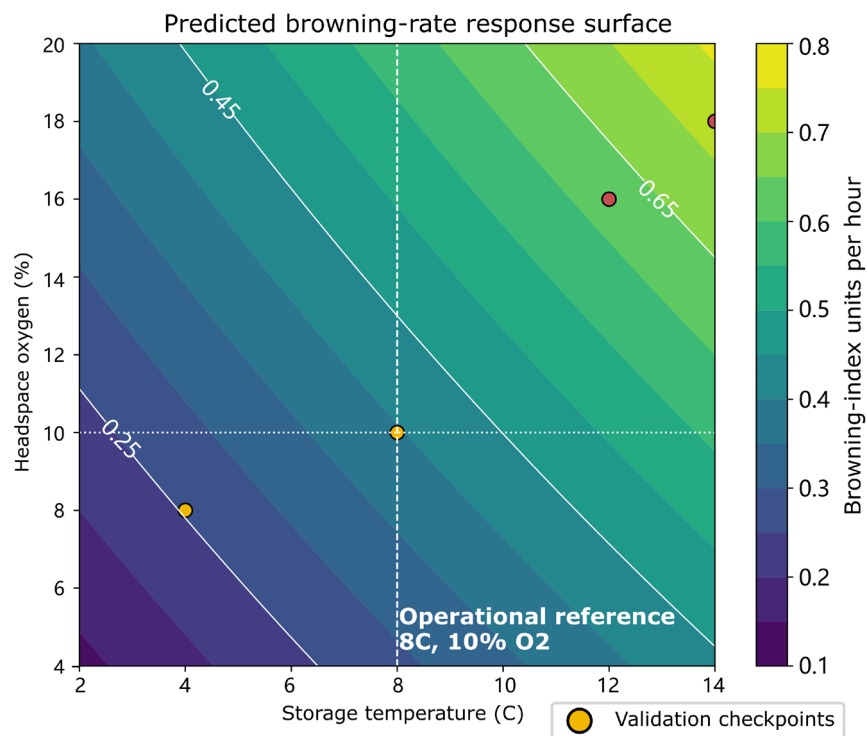


Figure 6. Physical-consistency response surface of predicted browning rate under temperature and oxygen availability.

Engineering Interpretation of Prediction Outputs

Engineering usefulness was investigated by shelf-life boundary prediction, batch ranking and early-warning stability. Shelf-life model studies frequently use the rejection-time error because process managers require an action window rather than just a regression value [31]. A batch was deemed unsuitable if the predicted browning index exceeded 35 or if the predicted freshness grade fell into the lowest category. Across 48 test batches, the proposed model estimated the rejection time with a median absolute error of 3.6 h, compared with 5.2 h for transformer, 6.1 h for LSTM, and 7.4 h for random forest. The box plot in Figure 7(a) shows a tighter shelf-life error range for the proposed method. The vegetable-specific warning bars in Figure 7(b) show precision above 88.6% and recall above 88.8% for all four categories.

The dual-output structure can be used by plant operators; continuous predictions of browning index support shelf-life estimation, and categorical freshness grades offer a direct decision label. Research on sensor fusion for postharvest quality monitoring has also shown the benefits of combining continuous and discrete quality indicators [32].

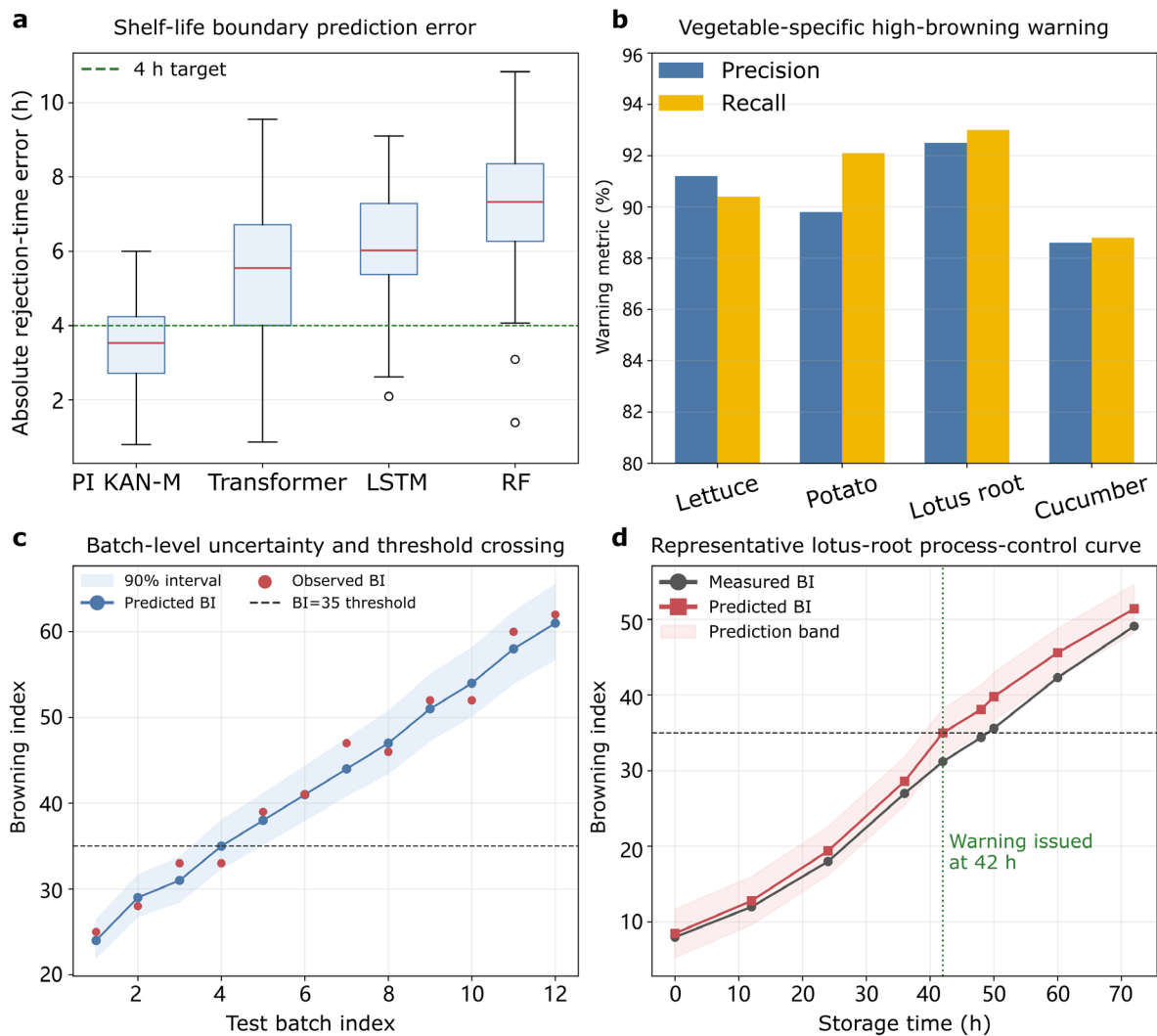


Figure 7. Engineering decision outputs: (a) shelf-life boundary error distribution; (b) vegetable-specific warning precision and recall; (c) uncertainty intervals for test batches; (d) process-control trajectory for a representative lotus-root batch.

Conclusion

This paper proposes a physics-informed KAN-Mamba model for browning prediction in fresh-cut vegetables. The above framework proposed a nonlinear KAN feature mixing, an efficient Mamba sequence model and a soft kinetic consistency constraint to capture the joint distribution of visual colour, spectral response, gas atmosphere, humidity, temperature and storage time. Based on the above experiments, embedding physical knowledge in the learning objective improved the stability of predictions and early-warning behavior under temperature fluctuations; at the same time, it maintained flexibility for all vegetable categories and processing batches.

Several Deficiencies Exist. The dataset contained four representative vegetables and three storage temperatures, but it did not cover all cutting geometries, anti-browning treatments, packaging films, and seasonal raw-material sources in industrial production. Surface dehydration and edge irregularity were only indirectly shown by image and humidity features, and thus had reduced accuracy for some cucumber and lettuce samples. Biochemical assays of enzyme activity, phenolic content and tissue structure were also omitted; therefore, the physical constraint should be regarded as an engineering premise rather than a full-fledged biochemical system.

Future work will expand the dataset to include more cultivars, processing lines and distribution scenarios, and add texture, surface-water and package-permeability descriptors for a more mechanistic interpretation. The

other way is online adaptation, and the model updates batch-specific parameters from the initial stored observations while keeping the global physical constraints unchanged. Integration of low-cost edge sensors and plant-level decision systems may provide a data stream suitable for large-scale physics-informed sequence learning.

Author Contributions

Iliana Trifunović contributes to conceptualization, methodology, software, validation, analysis, investigation, data collection, draft preparation, manuscript editing, visualization, supervision, project administration, and funding acquisition. Radojka Filipović contributes to validation, analysis, investigation, data collection, draft preparation. Tihomira Gojković contributes to analysis, investigation, data collection, draft preparation, manuscript editing. All authors have read and agreed with the manuscript before its submission and publication.

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Institutional Review Board Statement

Not applicable.

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