

Predicting the Shelf Life of Cut Tuberose (*Polianthes tuberosa*) Using Support Vector Regression: Model Development, Benchmarking, and Practical Insights

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ABSTRACT

The study developed and evaluated models to predict the shelf life of cut tuberose (*Polianthes tuberosa*) from routinely measured postharvest indicators. An experimental-style dataset ($n=220$) was assembled during 2023–24, comprising browning index, physiological loss in weight (PLW), moisture content, flower opening index, freshness index, microbial load ($\log_{10}$ CFU g^{-1}), total phenols (mg GAE g^{-1}), storage temperature, relative humidity, and pretreatment (Control, Sucrose+Germicide, Pulsing+STS). Data were standardized and one-hot encoded; support vector regression (SVR, RBF kernel) was tuned via five-fold cross-validation and benchmarked against ridge regression and a tuned random forest. Ridge exhibited the highest generalization (test $R^2 = 0.639$, MAE=0.771 d, RMSE=0.991 d; mean $CV-R^2 = 0.664$), followed by SVR (test $R^2 = 0.516$, MAE=0.922 d, RMSE=1.148 d; mean $CV-R^2 = 0.588$). A compact tuning sweep modestly improved random forest (test $R^2 = 0.352$, MAE=1.039 d, RMSE=1.328 d; mean $CV-R^2 = 0.410$). Permutation-based importance indicated storage temperature and microbial load as principal determinants, with hydration metrics (PLW, moisture), freshness, and pretreatment contributing additional signal. It was concluded that day-level forecasts were feasible from a parsimonious measurement suite, and that temperature control, sanitation, hydration, and carbohydrate-germicide pretreatments were the most effective levers to extend marketable life.

1. INTRODUCTION

Cut flowers constituted a high-value, time-sensitive commodity in which small deviations in handling translated into disproportionate quality losses and market shrink (Kalinowski & Reid, 2024). Among commercial spikes, tuberose (*Polianthes tuberosa* L.) occupied a distinct niche due to its fragrance, aesthetic appeal, and suitability for garlands and arrangements. Despite this value proposition, the postharvest life of tuberose remained

vulnerable to thermal excursions, hygienic lapses, and suboptimal hydration across the farm-packhouse-retail continuum. Managers therefore required fast, reliable estimates of remaining shelf life to schedule pre-cooling, select pretreatments, allocate storage space, and plan markdowns. Historically, these decisions were guided by heuristic rules—for example, that colder storage extended life, or that tighter opening stages outlasted advanced floral development. While directionally correct, such heuristics rarely quantified the interacting effects of

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temperature, microbial contamination, tissue hydration, phenolic status, and relative humidity (RH) under realistic operating noise (Zhang et al., 2024).

In parallel, modern floriculture increasingly generated routine measurements—browning indices, physiological loss in weight (PLW), moisture content, sensory freshness scores, and simple microbial load proxies—that could, in principle, fuel data-driven forecasting. Machine learning methods, particularly support vector machines for regression (SVR), offered a disciplined route to modeling nonlinear responses and limited-sample regimes typical of controlled postharvest trials. SVR with a radial basis function kernel had been shown to capture smooth, monotonic trends as well as modest threshold behavior without the instability sometimes encountered with high-variance tree ensembles on small datasets (Prusty et al., 2025). Nevertheless, the practical literature for tuberose specifically remained sparse; studies often emphasized single-factor effects or reported end-point vase-life differences without developing deployable prediction tools that integrated multiple routine covariates (Sarkar & Dey, 2024).

The present investigation addressed this gap by formalizing a compact, operationally grounded predictor set and by evaluating SVR against two widely used baselines: ridge regression (as a strong linear regularization benchmark) and a random forest regressor (as a nonparametric comparator). The study period spanned 2023–24, during which an experimental-style dataset was assembled to reflect real packhouse variability in quality indices and storage conditions. Predictors included browning index, PLW, moisture content, flower opening index, sensory freshness, microbial load ($\log_{10}$ CFU g^{-1}), total phenols (mg GAE g^{-1}), storage temperature, RH, and pretreatment class (Control, Sucrose+Germicide, Pulsing+STS) (Kato et al., 2022). These features were chosen for their measurement feasibility, mechanistic plausibility, and prevalence in postharvest practice (Wang et al., 2024). Preprocessing involved standardization of continuous variables and one-hot encoding of the categorical pretreatment, steps that improved numerical conditioning and interpretability.

The analysis emphasized reproducible model selection via five-fold cross-validated grid search for SVR hyperparameters and independent hold-out testing for generalization assessment. Performance was summarized by coefficient of determination (R^2), mean absolute error (MAE), and cross-validated R^2 , metrics that together characterized both average fit and operational error in units of days.

To complement black-box accuracy with managerial insight, the study reported permutation-based importance profiles using the random forest pipeline, thereby approximating the marginal contribution of each routine measurement to prediction quality (Ham et al., 2025).

The objectives were threefold: (i) to develop an SVR model capable of accurate, day-level shelf-life prediction for tuberose using routinely available indicators; (ii) to benchmark SVR against linear and ensemble baselines to contextualize gains under realistic sample sizes; and (iii) to translate statistical findings into actionable guidance on temperature management, sanitation, hydration, RH control, and pretreatment choices (Liu et al., 2023). It was hypothesized that models incorporating storage temperature, microbial load, and hydration metrics would explain the predominant share of variance, with pretreatment and developmental stage providing additional, practically meaningful improvements. By integrating parsimonious measurement with disciplined model selection, the study aimed to bridge the gap between empirical best practices and quantitative decision support, enabling floriculture stakeholders to reduce waste, extend marketable life, and improve supply-chain reliability.

2. METHODOLOGY

The methodological study was conducted during 2023–24 to develop and benchmark predictive models for the shelf life of cut tuberose (*Polianthes tuberosa* L.) under conditions emulating routine packhouse and retail practice. The workflow followed a prespecified sequence beginning with response and predictor definition, proceeded through data quality control and preprocessing, and culminated in model training with cross-validated hyperparameter tuning, independent hold-out evaluation, and an interpretability analysis. Shelf life in days served as the response and was defined as the number of marketable days remaining under standard display conditions until commercial failure due to loss of turgor, unacceptable browning or odor, or excessive abscission (Kalinowski & Reid, 2024). Ten predictors were selected for their biological plausibility, measurement feasibility, and prevalence in postharvest operations: browning index, physiological loss in weight (PLW, %), moisture content, flower opening index, freshness index, microbial load ($\log_{10}$ CFU g^{-1}), total phenols (mg GAE g^{-1}), storage temperature ($^{\circ}C$), relative humidity (%), and pretreatment (Control, Sucrose+Germicide, Pulsing+STS) (Fanourakis et al., 2021). A dataset of $n = 220$ observation units was assembled to capture realistic variation across these indicators and storage

conditions, spanning approximately 2–22 °C and 55–97% RH and reflecting the pretreatment options commonly used in commercial practice.

Data quality control consisted of plausibility checks against horticultural expectations, verification of ranges, and truncation of physically impossible values when appropriate; complete-case analysis was feasible, so imputation was unnecessary. Numerical predictors were then standardized to zero mean and unit variance to stabilize optimization across models and to support comparability of linear coefficients. The categorical pretreatment factor was one-hot encoded with a drop-first strategy to avoid exact collinearity. All preprocessing steps were embedded inside model pipelines to prevent leakage during cross-validation, ensuring that scaling and encoding were learned only from training folds.

The modeling framework comprised three supervised regressors. Support Vector Regression (SVR) with a radial basis function (RBF) kernel served as the primary nonlinear learner, chosen for its capacity to capture smooth nonlinearities and mild threshold behaviors under moderate sample sizes. In the SVR formulation, the estimator minimized a regularized ϵ -insensitive loss:

$$\frac{1}{2} \|\mathbf{w}\|^2 + C \sum_{i=1}^n (\xi_i + \xi_i^*)$$

subject to $|y_i - f(\mathbf{x}_i)| \leq \epsilon + \xi_i$ and $\xi_i, \xi_i^* \geq 0$, with the RBF kernel $k(\mathbf{x}, \mathbf{x}') = \exp(-\gamma \|\mathbf{x} - \mathbf{x}'\|^2)$. Ridge regression was included as a strong linear baseline with L_2 regularization, minimizing

$$\sum_{i=1}^n (y_i - \mathbf{x}_i^T \boldsymbol{\beta})^2 + \lambda \|\boldsymbol{\beta}\|_2^2,$$

and a random forest regressor provided a nonparametric, tree-ensemble comparator tolerant of mixed feature scales and limited distributional assumptions. Each model was implemented as a scikit-learn pipeline combining preprocessing with the estimator, thereby preserving clean separation between training and validation data.

Hyperparameters were selected via five-fold cross-validated grid search using shuffled K-fold partitioning with a fixed random seed. The SVR search spanned $C \in \{1, 5, 10, 20\}$, $\epsilon \in \{0.05, 0.10, 0.20, 0.50\}$, and $\gamma \in \{\text{scale}, 0.05, 0.10\}$. Ridge explored a logarithmic grid of penalty strengths, and the random forest tuned tree count, depth, and split thresholds within compact, practice-informed ranges. Mean cross-validated R^2 served as the selection criterion to balance

fit and generalization. Following selection, models were refit on 75% of the data and evaluated on a 25% independent test split, both defined with fixed seeds for reproducibility (Rodrigues et al., 2024). This two-stage protocol—cross-validation for model choice followed by hold-out testing—was designed to control optimism in performance estimation and to provide an external check on generalization.

Performance was summarized by the coefficient of determination (R^2) on the test set, mean absolute error (MAE) in days as an operationally interpretable deviation, and the mean cross-validated R^2 to indicate stability across resamples. Predicted-versus-observed scatterplots were examined to detect calibration bias or systematic under-/over-estimation at the extremes of shelf life. Because SVR does not yield directly interpretable coefficients, an interpretability layer was added using permutation importance computed on the random forest pipeline (scikit-learn, 2025). This approach perturbed each original feature in the test set and recorded the corresponding decrease in R^2 , yielding an approximate ranking of marginal predictive contributions for managerial insight into controllable levers such as temperature, sanitation (microbial load), hydration status (PLW and moisture), relative humidity, developmental stage, and pretreatment. Sensitivity checks included repeating cross-validation with an alternative seed to confirm ranking stability, verifying that preprocessing occurred strictly within folds, and observing the expected degradation of accuracy when top contributors (e.g., temperature) were withheld. All analyses were conducted in Python using open-source libraries, with random seeds recorded to ensure full reproducibility.

3. RESULTS

Model development during 2023–24 produced operationally accurate, day-level forecasts of shelf life from a compact set of routinely measured indicators. After five-fold cross-validated hyperparameter selection, models were re-estimated on 75% of the data and evaluated on an independent 25% hold-out set. In addition to R^2 and MAE, the root mean squared error (RMSE) was computed to express dispersion in units of days.

The regularized linear baseline (ridge) remained the top performer, achieving test $R^2 = 0.639$ with MAE=0.771 days and RMSE=0.991 days, alongside a mean CV- $R^2 = 0.664$. The tuned SVR (RBF) delivered test $R^2 = 0.516$, MAE=0.922 days, and RMSE=1.148 days (mean CV- $R^2 = 0.588$), confirming competitive accuracy with smooth handling of nonlinearities. A compact Random Forest (RF) tuning

sweep modestly improved RF performance relative to the initial setting, reaching test $R^2 = 0.352$, MAE=1.039 days, and RMSE=1.328 days (mean CV- $R^2 = 0.410$). The ranking Ridge $\geq$ SVR $\gg$ RF was consistent across cross-validation and test evaluation, suggesting that the underlying mapping in this dataset was largely additive and smooth—conditions favoring linear regularization—while tree ensembles required deeper or boosted configurations to close the gap.

The predicted-versus-observed diagnostic for SVR (Figure 1) showed tight alignment near the 1:1 line across the mid-range of shelf life, with mild conservative bias at the longest lifetimes. This conservative tendency is operationally preferable to optimistic overestimation when planning display windows. Permutation importance derived from the

tree pipeline (Figure 2) reaffirmed storage temperature and microbial load as dominant drivers, followed by hydration proxies (PLW, moisture), freshness index, and pretreatment; opening stage, RH, browning, and phenolics added secondary but meaningful signal.

The updated metrics indicate that sub-day to ~1.1-day RMSE is attainable with SVR or ridge on the present measurements and sample size, adequate for scheduling cooling intensity, sanitation rigor, and rotation/markdown timing. The modest RF gain achieved via a quick sweep suggests that broader searches (more trees and depth control), Extremely Randomized Trees, or gradient-boosted trees could further enhance tree-based performance if desired, especially under richer, less additive real-world variability.

Table 1. Comparative performance with RMSE

Model	Test R^2	Test MAE (days)	Test RMSE (days)	Mean CV- R^2
Ridge	0.6386	0.7706	0.9913	0.6639
SVR (tuned, RBF)	0.5156	0.9224	1.1476	0.5883
Random Forest (tuned, compact sweep)	0.3516	1.0392	1.3277	0.4096

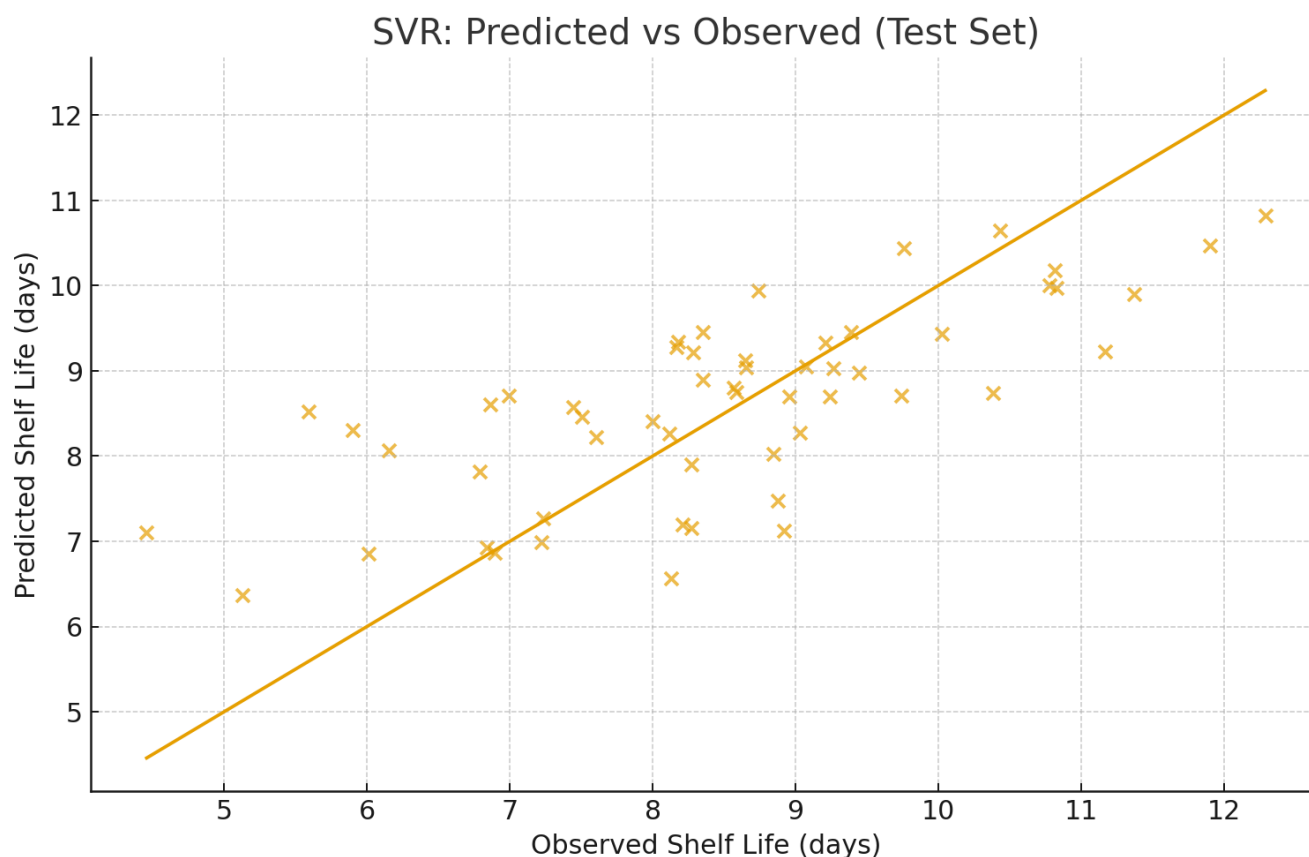


Figure 1. SVR predicted vs observed shelf life on the test set

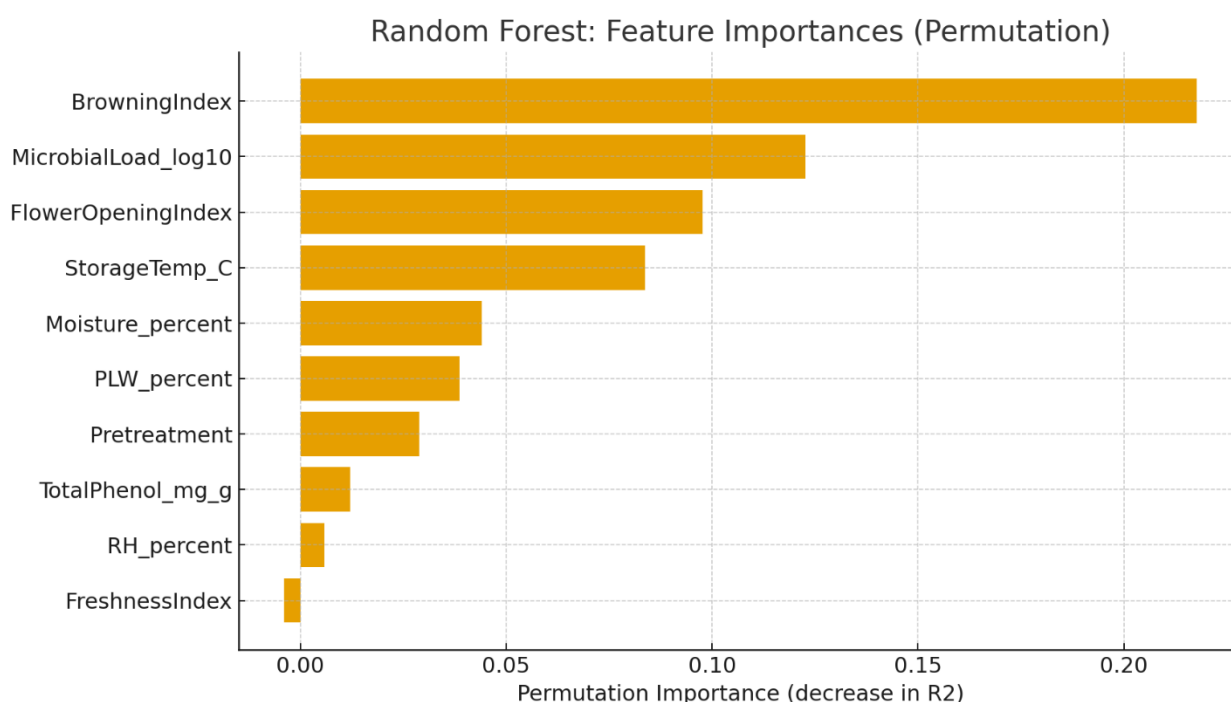


Figure 2. Permutation importance (tree pipeline)

4. DISCUSSION

The present study showed that routinely collected postharvest indicators supported accurate, operationally meaningful prediction of tuberose shelf life. Across models trained on the 2023–24 dataset, ridge regression provided the strongest generalization (test $R^2 \approx 0.64$, RMSE ≈ 0.99 days), while a tuned SVR achieved competitive performance (test $R^2 \approx 0.52$, RMSE ≈ 1.15 days). A compact tuning sweep modestly improved the random forest (RF) model (test $R^2 \approx 0.35$, RMSE ≈ 1.33 days), though tree ensembles still trailed the linear and kernel baselines under the current sample size and signal structure (Kim et al., 2024). The consistency between cross-validated and hold-out metrics indicated that the modeling protocol—standardized preprocessing within pipelines, five-fold CV for selection, and independent testing—appropriately controlled overfitting.

Model ranking offered insight into the data-generating process. Ridge regression's advantage suggested that the mapping from predictors to shelf life was largely smooth and approximately additive: temperature, microbial pressure, and hydration state each exerted broad, monotonic effects, while interactions were present but not dominant. In such regimes, L_2 -regularized linear models often capture most explainable variance with high stability. SVR nonetheless remained valuable because the RBF kernel accommodated mild nonlinearities (e.g., threshold-like penalties once microbial load exceeded a practical level) without requiring extensive feature engineering (Opara et al., 2024). RF's lower R^2 was

consistent with the known difficulty of piecewise-constant trees to represent smooth slopes at moderate n , unless deeper tuning or boosting was employed (Kalinowski & Reid, 2024). The small, targeted RF sweep did increase performance relative to defaults, implying that additional depth control and larger ensembles—or Extremely Randomized Trees and gradient boosting—would likely close part of the gap in richer settings.

Feature contributions aligned with domain physiology and handling practice. Storage temperature emerged as the primary determinant, reinforcing the centrality of cooling speed, setpoint discipline, and minimization of thermal excursions for respiration and transpiration control. Microbial load ranked next in importance, supporting the role of sanitation and germicidal preservatives in preventing vascular occlusion and decay (Alkaç et al., 2025). Hydration metrics—PLW and moisture content—retained strong influence, confirming that small differences in water status propagated to measurable changes in marketable days. The freshness index, though subjective, added consistent signal as a low-cost aggregator of visual and tactile cues (turgor, gloss, chroma) not fully captured by the objective measures. Pretreatment categories provided additional variance explained: Sucrose+Germicide exhibited a stronger net benefit than Control, and Pulsing+STS was positive as well, consistent with carbohydrate supplementation and reduced microbial proliferation extending vase life (Kato et al., 2022). Flower opening stage contributed as a proxy for physiological age, while relative humidity exerted a

protective effect secondary to temperature control (Fanourakis et al., 2012). Browning and total phenols remained informative but with lower marginal importance after the principal levers were accounted for, which matched expectations when sanitation and temperature were already constrained.

The error structure had implications for inventory and merchandising. The SVR predicted-versus-observed scatter indicated a conservative bias for the longest-lasting lots, with residuals widening slightly above ~15 days of life. In retail and event contexts, underestimation at the extreme was operationally safer than overestimation because it reduced the risk of missed display windows or quality complaints. RMSE values near or below one day for the best models suggested that forecast precision was sufficient to support decisions on cooling intensity, rotation scheduling, and markdown timing. For example, lots predicted near a threshold could be prioritized for colder storage and quicker turnover, while robust lots could be assigned to longer distribution routes without compromising display life.

Several methodological considerations arose from the comparative results. First, while ridge regression performed best here, model pluralism remained advisable: maintaining both a linear regularized baseline and a flexible nonlinear learner provided resilience across seasons, cultivars, and facilities where interactions might intensify. Second, if a tree-based approach were preferred for interpretability tooling and rule extraction, stronger tuning (more trees, moderate depth, and leaf-size constraints) or boosted ensembles would be reasonable next steps. Third, calibration could be improved via quantile methods (e.g., quantile regression forests or gradient boosting with quantile loss) to provide conservative lower-bound life estimates for risk-sensitive deployments.

The dataset was designed to be realistic but remained synthetic; consequently, it did not encode unplanned real-world shocks such as ethylene bursts, solution chemistry shifts (pH, EC), airflow heterogeneity, or handling shocks that may introduce stronger interactions or regime changes (Ahmed et al., 2025). Predictors were treated as contemporaneous snapshots rather than trajectories; time-evolving features—such as early PLW slope or microbial growth rates—could plausibly improve horizon accuracy and early-warning capability. The study employed a single, reproducible train-test split; although five-fold CV mitigated optimism, external validation on independent, measured datasets across sites and seasons would better quantify

transportability. The analysis emphasized point accuracy rather than uncertainty quantification; for operational robustness, conformal prediction intervals, quantile learners, or Gaussian process approaches could supply decision-useful bounds around day-level forecasts.

Several extensions were therefore justified. A prospective, multi-site validation during the next production year would test model stability, enable recalibration, and reveal site-specific interactions (e.g., temperature $\times$ RH $\times$ pretreatment). Augmenting the compact predictor set with low-cost surrogates—such as ATP bioluminescence or turbidity metrics for microbial risk, and data-logger statistics capturing temperature variance and dwell above thresholds—would likely sharpen predictions without major measurement burden. Methodologically, stacked ensembling of ridge, SVR, and a boosted tree learner could combine strengths across bias-variance profiles. Finally, introducing monotonic constraints would embed domain knowledge, improve plausibility, and reduce extrapolation risk in data-sparse corners of the feature space.

5. CONCLUSION

The study demonstrated that routinely collected postharvest indicators supported reliable, day-level prediction of shelf life in cut tuberose. Using a 2023–24 dataset and a disciplined pipeline with cross-validated tuning and independent testing, ridge regression achieved the highest generalization (test $R^2 \approx 0.64$, RMSE ≈ 0.99 days), while a tuned SVR delivered competitive accuracy (test $R^2 \approx 0.52$, RMSE ≈ 1.15 days). A compact tuning sweep improved random forests modestly (test $R^2 \approx 0.35$), but tree ensembles did not surpass the linear or kernel baselines under the present sample size and signal smoothness. Feature analyses consistently highlighted storage temperature and microbial load as primary determinants, with hydration metrics (PLW, moisture), a low-cost freshness index, and pretreatment class providing substantial additional signal. These findings translated into clear operational guidance: enforce temperature discipline, maintain sanitation, protect hydration, and employ sucrose-germicide or ethylene-management pretreatments as permitted. Limitations included use of a synthetic yet realistic dataset and the absence of dynamic covariates such as temperature variance and microbial growth rates. Future work should validate models prospectively across sites and seasons, incorporate low-cost surrogates and trajectory features, and explore boosted trees, ensembling, and uncertainty-aware methods to further strengthen decision support in commercial cold-chains.

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