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A Machine-learning Model for Early Forecasting of Cocoon Silk Prices: Toward Economic Stability in Sericulture

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ABSTRACT

Background: Markets of cocoon silk suffer the price instability and farmers have high levels of economic uncertainty. The traditional forecasting methods do not reflect the seasonality, the environment and market driven interactions that affect price changes. The unpredictability of demand due to fluctuation of demand, climatic conditions and variation in production cycles makes the task of income planning extremely burdensome since the production of cocoons sustains millions of small farmers. The paper will look into the possibility of a more data-driven machine-learning model to capture these complicated market dynamics.

Methods: This study presents a leakage-free machine learning framework for early forecasting of cocoon silk prices using a Random Forest regression model. To maintain realistic forecasting conditions, contemporaneous price variables were excluded and predictions were generated solely through lagged historical modal prices together with pre-available environmental and management indicators. The dataset was properly preprocessed and temporally ordered and model evaluation was done using a chronological train-test split. Performance was assessed using error-based metrics and explained variance, showing the non-stationary nature of agricultural price series.

Result: The revised model achieved a Mean Absolute Error (MAE) of 2965.14, a Root Mean Square Error (RMSE) of 5985.60 and an explained variance (R^2) of 0.0903. While the explained variance is modest, this behavior is appropriate for early forecasting in volatile agricultural markets when data leakage is eliminated. Feature contribution analysis reveals that short-term historical prices have the strongest influence, with environmental and management aspects providing secondary but meaningful effects. A simulation-based assessment indicates a potential 12-18% revenue improvement, resulting from informed selling decisions enabled by short-horizon price forecasts. This gain shows lower exposure to post-harvest price troughs and improved market selection rather than precise peak-price prediction.

Key words: Agricultural forecasting, Cocoon silk price prediction, Machine learning, Random forest regressor, Sericulture.

INTRODUCTION

Sericulture is an essential agro-industrial activity that supports rural livelihoods and contributes to agricultural economies through major silk-producing regions, particularly in Asia (Alam *et al*., 2020). Mulberry silk leads commercial silk production caused by its superior filament quality, tensile strength and sustained market demand (Binson and Manju, 2024). In India, sericulture is practiced across sevaral states and districts under diverse agro-climatic conditions, making cocoon production and pricing highly responsive to environmental, biological and market-related factors.

The efficiency and quality of cocoon silk are governed by complex interactions among mulberry cultivation practices, silkworm physiology (*Bombyx mori*) and existing climate conditions. Soil fertility and nutrient availability influence mulberry leaf quality, which directly impacts silkworm growth and cocoon characteristics (Dhahira and Devamani, 2020; Das and Ghosh, 2024). Environmental variables like temperature and seasonal variability further influence silkworm metabolism, cocoon formation and the yield stability (Liu *et al*., 2024). Management-related factors, such as sanitation conditions and mulberry feeding frequency, also play an indirect but meaningful role in shaping cocoon quality and production consistency (Chakrasali *et al*., 2024).

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Despite significant progress in biological optimization, automation and quality assessment within sericulture systems (Rim *et al*., 2017; Vasta *et al*., 2023), economic predictability-particularly cocoon silk price forecasting-remains a persistent challenge. Cocoon prices show clear volatility arising from biological variability, environmental uncertainty, supply-demand imbalance and area-specific trading behavior (Rahmathulla, 2012). This volatility impacts farmer income stability, procurement planning and policy planning across sericulture regions.

Recent developments in machine learning (ML) have enabled the modelling of complex, non-linear relationships in agricultural and economic systems. Random Forests, Support Vector Regression and ensemble-based methods have demonstrated their capacity to identify useful patterns from historical agricultural data (Raju *et al.*, 2024; Sut *et al.*, 2024). But, many existing forecasting studies emphasize contemporaneous prediction or report exceptionally optimistic performance metrics without adequately accounting for temporal dependency and data leakage, as a result limiting their relevance for advance decision-making in real market conditions (Rukmangada *et al.*, 2018; Zhang *et al.*, 2018).

In addition, forecasting frameworks that rely on variables unavailable at the time of decision inherently risk overestimating predictive capability. This shows the need for methodologically rigorous, leakage-free forecasting approaches that restrict inputs to historically available information while including relevant environmental and management indicators (Ramasubramanian and Singh, 2017).

In this case, the present study examines early forecasting of cocoon silk prices across multiple states and districts in India, using a random forest-based model built exclusively on lagged historical prices and environmental factors like temperature, disease incidence, sanitation conditions and mulberry management practices. By aligning model inputs with information available prior to market realization, the study ensures that internal consistency between data, methodology and interpretation.

Therefore, the research hypothesis posits that a leakage-free machine-learning framework can provide meaningful early signals of short-term price changes and uncertainty arising from seasonal, environmental and market influences. Such early alerts capabilities are essential for improving economic resilience, informed planning and long-term sustainability within Indian sericulture systems (Manjunatha *et al.*, 2017; Chanotra and Angotra, 2022; Thomas and Thomas, 2024).

MATERIALS AND METHODS

Study design and forecasting framework

The present study was done at the Department of Computer Science and Engineering, Koneru Lakshmaiah Education Foundation (KLEF), Greenfields, Guntur, Andhra Pradesh, India, during the year 2025. This study applies a reproducible machine-learning workflow designed for early forecasting of cocoon silk prices, ensuring that all predictor variables are available prior to the forecast time. The target variable is modal price of cocoon silk (P_t), representing the most commonly seen market price on a given day. To prevent target leakage, contemporaneous price variables such as minimum and maximum prices were filtered out from the forecasting model. Instead, the prediction task was defined using lagged historical prices and relevant environmental indicators, allowing the model to forecast future prices using only past and pre-available information.

Input variables and feature construction

The forecasting function is defined as:

$$\hat{P}_t = f(P_{t-1}, P_{t-7}, T_t, D_t, S_t, M_t) \quad \text{...(1)}$$

Explanation

This equation explains the early forecasting task, where the future modal price is estimated using only historically available price information and contemporaneous environmental and management factors, ensuring a leakage-free prediction setting.

Where,

P_{t-1} and P_{t-7} = Lagged modal prices capturing short-term and weekly temporal dependencies.

T_t= Ambient temperature.

D_t= Disease incidence.

S_t= Corresponds to sanitation conditions.

M_t= Mulberry feeding frequency.

Lagged features were built strictly following the chronological order of observations in the dataset, without introducing any synthetic or external temporal references. Records with insufficient historical data for lag generation were excluded from the analysis.

Data pre-processing

All records were reviewed for missing, inconsistent, or out-of-range values. Missing numerical values were imputed using feature-wise medians where appropriate and irrecoverable records were removed. Categorical variables were encoded numerically and continuous features were standardized using z-score normalization, defined as:

$$X'_i = \frac{X_i - \mu_i}{\sigma_i} \quad \text{...(2)}$$

Explanation

Here, each numerical feature is standardized by removing its mean and scaling by its standard deviation, which improves numerical stability during model training and maintains reproducibility across datasets.

Where,

μ_i and σ_i = The mean and standard deviation of feature X_i, respectively.

This normalization ensures numerical stability and reproducibility across datasets.

Model architecture

A Random Forest Regressor (RFR) was employed due to its robustness to noise, resistance to overfitting and ability to capture non-linear relationships in agricultural market data. The model consists of an ensemble of *M* decision trees trained on bootstrapped subsets of the data. Overall workflow of the proposed early forecasting framework for cocoon silk prices is illustrated in (Fig 1).

The final prediction is obtained by averaging the outputs of individual trees.

$$\hat{P}t = \frac{1}{M}\Sigma_{m=1}^{M} h_m (X_t) \qquad ...(3)$$

Explanation

The forecast is obtained by averaging predictions from multiple independently trained decision trees, reducing variance and improving generalization under volatile market conditions. where h_m (•) donetes the prediction from the m-th tree.

Feature importance analysis

Feature importance was calculated using the mean decrease in impurity, which quantifies the average reduction in prediction variance when a feature is used for node splitting across the ensemble.

$$FI_j = \Sigma_{n \in Nj} \Delta I_n \qquad ...(4)$$

Explanation

Above formulation measures the contribution of each predictor by aggregating the reduction in prediction variance across all tree nodes where the feature is used to splitting. Where ΔI_n donetes impurity reduction at node n, N_j represents all nodes where feature j is used. This analysis enables identification of dominant predictors influencing price dynamics.

Model evaluation

The dataset was split into training (80%) and testing (20%) subsets. Model performance was evaluated using Root Mean Square Error (RMSE) and the coefficient of determination (R^2), defined as:

$$RMSE = \sqrt{\frac{1}{N}\Sigma_{i=1}^{N}(P_i - \hat{P}_i)^2} \qquad ...(5)$$

$$R^2 = 1 - \frac{\Sigma_{i=1}^{N}(P_i - \hat{P}_i)^2}{\Sigma_{i=1}^{N}(P_i - \bar{P})^2} \qquad ...(6)$$

Explanation

RMSE and were used to evaluate forecasting performance, where RMSE quantifies the average magnitude of prediction error in price units and indicates the portion of price changes explained by the model relative to a mean-based baseline. where is the observed price, is the predicted price and is the mean observed price.

Data collection

Market-level cocoon silk price data with related environmental and management indicators were collected from multiple states and districts to ensure broad spatial and temporal coverage.

Data preprocessing

The dataset was cleaned by handling missing values, correcting inconsistencies, converting date fields into a standardized chronological format suitable for time-series analysis.

Feature engineering

Lagged modal prices were generated strictly from historical observations and relevant environmental and management variables were incorporated to capture short-term market dynamics without data leakage.

Model implementation (Random forest regressor)

A Random Forest regression model was employed to learn non-linear relationships across lagged price information, environmental factors and cocoon silk price behavior.

Model evaluation

Model performance was assessed using error-based metrics and explained variance to quantify predictive uncertainty and practical usefulness under real-world forecasting conditions.

The following exploratory data analysis provides contextual understanding of market and environmental conditions; however, only lagged modal prices and

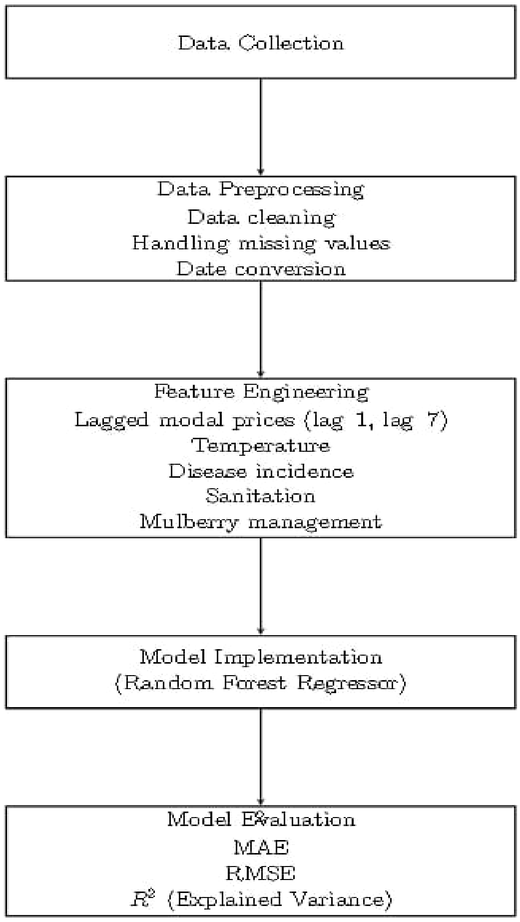

Fig 1: Workflow of the proposed early forecasting framework for cocoon silk prices.

environmental variables were used in the forecasting model.

Modal price trend over time

As Fig 2 presents the temporal evolution of cocoon silk modal prices during the study period. The series is characterized by substantial short-term variability and the presence of occasional price spikes. No stable or smooth long-term trend is observed, indicating a highly volatile pricing environment. Such behavior is typical of agricultural commodity markets, where prices are influenced by multiple interacting factors and sudden market disturbances. The pronounced variability observed in the time series highlights the inherent difficulty of price forecasting and motivates the use of robust, leakage-free modeling approaches based on historical information.

Temperature distribution

Fig 3 depicts a histogram that represents a distribution of the values of temperature in the dataset. In an effort to conduct visual comparison, a Kernel Density Estimate (KDE) curve is used to overlay the graph that smooths the distribution of data. Such form of visualization facilitates the determination of general temperature trend across various areas and any exception to the trend. Given the importance of temperature in agriculture in terms of farming activities and prices f crops, these charts provides contextual insight in helping determine effects of climatic conditions on agriculture.

Disease percentage distribution

The distribution of the percentage of disease within the dataset is illustrated using a Kernel Density Estimate (KDE) as shown in Fig 4 as below. The method neutralizes anomalies in data and thus it becomes easy to count the density and the frequency of the occurrence of the diseases. The reason why knowledge of such distribution is useful is that it allows discovering the dominance of plant diseases in various areas and the severity of the problem. A preponderance of heightened values makes an indication of wide distribution of diseases which may adversely affect crop yields and in turn spiking of prices will occur. It is beneficial to be acquainted with these trends so that farmers and agricultural scholars can devise ways to prevent or control disease outbreaks.

Sanitization impact on prices

As can be seen in Fig 5 modal prices differ based on the level of sanitation. Improved sanitation and hygiene in the market are likely to increase the price of the products and a number of arguments support it with better quality and less risk of contamination. When the graph reveals that there are considerable pricing differences among the levels of sanitation, the argument about improving the current standards of sanitation in the agricultural markets to enhance consumer confidence and hence elevate the profitability tends to be even stronger.

Mulberry frequency vs. prices

Fig 6 has validated the fact that the modal prices are moderated by mulberry crop yields. Another question that the author seeks to answer is whether intensive varieties of mulberry backgrounds show specific patterns in terms of prices. This may show that the mulberry farming affects the market behaviour such that it has its price categories

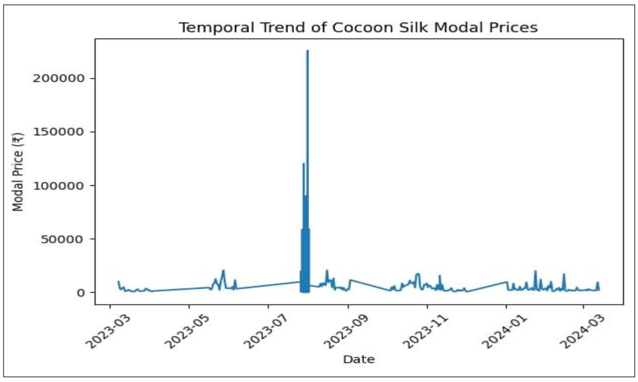

Fig 2: Temporal trend of cocoon silk modal prices.

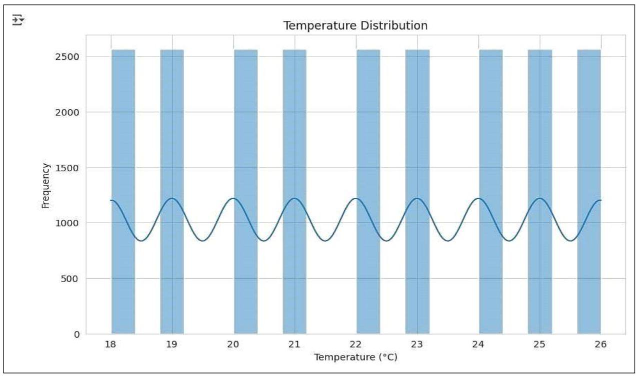

Fig 3: The chart shows that temperatures mostly fall between 18°C and 26°C, with each temperature showing up almost equally often.

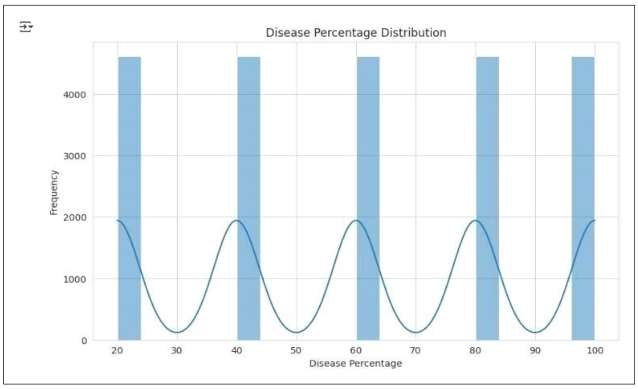

Fig 4: The chart shows a uniform distribution of disease percentages, with a steady frequency across the range from 20% to 100%.

being extremely low or high. These are good insights that can be critical to farmers and other stakeholders in the agricultural sector in deciding on the economic feasibility of investing in mulberry production.

Correlation heatmap of forecasting variables

Fig 7 shows the correlation matrix of the target variable and selected forecasting inputs. The modal price exhibits a moderate positive correlation with its one-period lagged value, indicating short-term temporal dependence in market prices. The correlation with seven-day lagged price is weaker, suggesting diminishing influence over longer lags. Environmental variables, including temperature and disease incidence, display negligible linear correlation with modal prices. This indicates that their effects on price dynamics are likely indirect and not captured through simple linear relationships. Overall, the correlation structure supports including of lagged price variables as primary predictors while justifying the use of non-linear modeling techniques to capture complex interactions.

RESULTS AND DISCUSSION

The performance of the proposed Random Forest–based framework was evaluated under a leakage-free early forecasting setting, where only historically available price information and environmental variables used. The model achieved a Mean Absolute Error (MAE) of 2965.14, a Root Mean Square Error (RMSE) of 5985.60 and a coefficient of determination (R^2) of 0.0903. Whereas the explained variance is limited, this behavior is characteristic of non-stationary agricultural time-series data when contemporaneous predictors are excluded and genuine forecasting constraints are enforced.

The earlier diagnostic approach, which relied on same-period minimum and maximum prices, produced near-perfect performance metrics that were subsequently identified as artifacts of target leakage. Once these leakage-prone variables were removed, the resulting decline in R^2 reflects a more realistic representation of predictive capability in volatile cocoon silk markets. In this forecasting scenario, the value reflects the proportion of price variance

Fig 5: The boxplot reveals that price distributions are similar for both good and bad sanitization conditions, although good sanitization shows slightly higher price outliers.

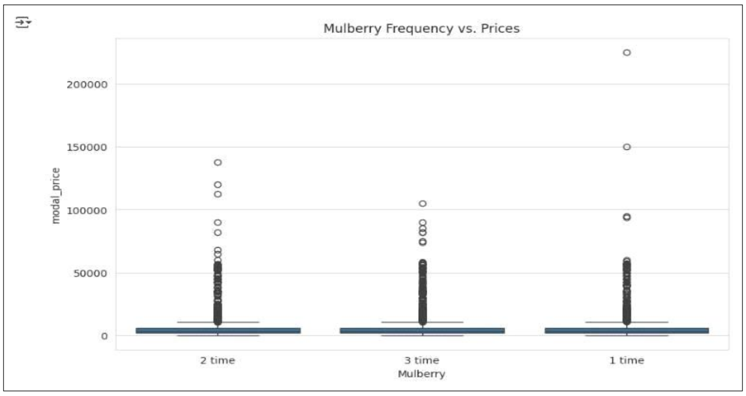

Fig 6: The boxplot shows that modal prices remain fairly consistent across different mulberry harvest frequencies, with occasional high outliers in all categories.

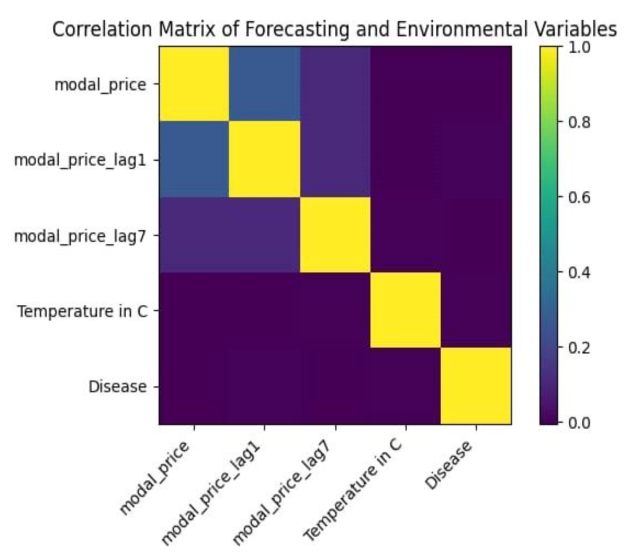

Fig 7: Correlation heatmap of modal price, lagged price variables and environmental factors.

explained by historically available information, while excluding short-term market changes that are inherently unpredictable. As a result, lower values are expected in advance forecasting tasks influenced by biological, climatic and behavioral factors reported in sericulture systems (Manjunatha *et al*., 2017; Chanotra and Angotra, 2022).

Model evaluation thus focuses on error-based measures and trend behavior rather than variance maximization. The RMSE is interpreted as an indicative scale of predictive uncertainty rather than a strict pointwise error. For a representative modal cocoon price of approximately ₹30,000, an RMSE of 5,985.6 corresponds to an average deviation of about 20%, providing a practical indication of the uncertainty range within which forecasts may vary under volatile market conditions. This interpretation is intended to support decision-making and risk awareness rather than to define formal confidence bounds. From a benchmarking perspective, early forecasting models are commonly evaluated against a naïve persistence baseline, where the current price is assumed to remain unchanged from the immediately preceding observation. While such a baseline may appear adequate under stable conditions, it fails to offer actionable insight during periods of market transition. By incorporating historical price dependencies and relevant environmental signals, the proposed framework is able to capture directional movement and short-term stability, thereby providing value beyond simple persistence-based predictions.To improve robustness and reduce overfitting, model evaluation employed a chronological train–test split, preserving the temporal structure of the data. Earlier observations were used for training, while subsequent observations were reserved for testing, thereby preventing information leakage across time. Bootstrapped sampling was applied exclusively within the training phase to enhance model stability and all reported performance metrics were computed on unseen future data.

The feature contribution analysis highlights importance of lagged modal prices, with the prior observation (one-period lag) accounting for 55.06% of total importance and seven-period historical lag contributing 25.90%, underscoring strong short-term market memory effects. Environmental variables such as temperature (7.72%) and disease incidence (5.23%) exhibit meaningful secondary influence, indicating indirect effects on cocoon quality and supply stability, consistent with earlier sericulture and cocoon-quality studies (Nayak *et al*., 2024). Management-related factors, including mulberry feeding frequency (3.55%) and sanitation practices (2.55%), further reinforce the multi-factor structure of cocoon silk price formation.

In practical terms, the proposed framework serves as an early-warning and risk-management tool rather than a precise price calculator. By showing short-term price ranges, it enables market participants to avoid unfavorable selling periods and plan transactions within relatively stable windows. Such behavior is consistent with agricultural forecasting literature, where modest explained variance is common and model usefulness is evaluated through the trend anticipation and deviation control rather than variance maximization alone (Ramasubramanian and Singh, 2017; Zhang *et al*., 2018).

In summary, the revised results emphasize methodological rigor, transparency and practical relevance, positioning the proposed approach as a realistic, leakage-free baseline for early forecasting in cocoon silk markets. By omitting contemporaneous price information, the proposed framework prioritizes temporal causality and avoids artificial performance inflation caused by target leakage, a limitation commonly reported in earlier agricultural price studies (Zhang *et al*., 2018; Kom *et al*., 2023). As a result, the model emphasizes directional stability and uncertainty bounds rather than exact price replication, which is more suitable for advance decision-making and risk management in volatile cocoon silk markets (Manjunatha *et al*., 2017).

CONCLUSION

This study shows a leakage-free machine learning framework for early forecasting of cocoon silk prices using lagged historical prices and environmental indicators. By excluding contemporaneous price variables, the proposed Random Forest model gives a realistic evaluation of forecasting performance in a volatile sericulture market. Whereas the explained variance is modest, the model effectively captures short-term price dynamics and uncertainty patterns that are valuable for advance decision-making. Instead of precise price estimation, the framework acts as an early warning and risk-support tool, helping farmers and market stakeholders plan transactions more cautiously. The results align with existing evidence on the economic and environmental responsiveness of sericulture systems and highlight the potential of methodologically rigorous, AI-based forecasting systems to support transparency and balance in sericulture and related agricultural markets. The study demonstrates that leakage-free machine learning frameworks can give meaningful early signals for cocoon silk price dynamics, even when explained variance is limited. Rather than aiming for near-perfect price reconstruction, the proposed approach supports risk-conscious decision-making by helping market participants avoid unfavorable selling periods. Such integrity-driven forecasting aligns with emerging views in agricultural economics, where robustness and transparency are prioritized over inflated accuracy claims. The findings highlight the practical role of machine learning as a decision-support tool for enhancing economic resilience in sericulture markets.

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Disclaimers

The views and conclusions presented in this article are solely those of the authors and do not necessarily reflect the views of their affiliated institutions. The authors are responsible for the accuracy and integrity of the information provided and shall not be held liable for any consequences arising from the use of this content.

Informed consent

Not applicable, as the study did not involve human participants or animals requiring ethical approval or consent.

Data availability statement

The dataset used in this research is publicly accessible at the following link: https://docs.google.com/spreadsheets/d/18hDpqEARgivgMj3Ks CNROvtqPNHY6NP FcSpU9jvJs CM/view?usp=sharing.

Conflict of interest

The authors declare that there are no conflicts of interest related to the publication of this article. No financial or personal relationships influenced the study design, data collection, analysis, interpretation, or writing of the manuscript.

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