Indian J Dairy Sci 78(4): 328-334
https://doi.org/10.33785/IJDS.2025.v78i04.005

RESEARCH ARTICLE

Prediction modelling of *Kulfi* freezing: A regression analysis approach

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Received: 17 February 2024 / Accepted: 31 July 2024 / Published online: 23 August 2025

Abstract: *Kulfi* is a popular frozen dessert that originated on the Indian subcontinent. Its distinct tastes and texture are a result of the intricate interaction between various ingredients and freezing dynamics. The act of freezing has a crucial role in sculpting the crystalline composition and sensory characteristics of *kulfi*, hence impacting its overall quality. It becomes crucial to maintain the exact control over freezing conditions in order to maintain the tastes and creamy quality that characterize this traditional treat. It is essential for maximizing production procedures, guaranteeing consistency in product quality and raising overall manufacturing efficiency in the food industry. A useful technique for figuring out the complex links controlling freezing behaviour is regression modelling. Regression modelling in the field of food science has been extensively studied; however there is still a significant study void in the area of *kulfi* freezing dynamics. Regression modelling is used in this work to specifically target the *kulfi* freezing domain in an effort to close this gap. The goal is to create a reliable regression model, using the temperature dynamics of *kulfi* samples as a basis, can forecast refrigerator air temperature with accuracy. The created regression model exhibits excellent prediction accuracy (Mean residual of 0.02°C) and offers a numerical framework for performance assessment ($R^2 = 0.999$, RMSE = 0.46, MSE = 0.21 and MAE = 0.20). This research provides a scientific foundation for implementing precise temperature prediction protocols in kulfi production, potentially leading to advancements in frozen dessert manufacturing techniques.

Keywords: Freezing, *kulfi*, regression modelling, temperature prediction

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Introduction

Indian subcontinental cuisine is known for its delicious frozen dessert *kulfi*, which is valued for its distinct tastes and velvety texture. *Kulfi* is often divided into two phases: dispersed and continuous. An unfrozen solution, an emulsion and a suspension of particles in liquid make up the continuous phase. The unfrozen solution is composed of water, sugar, hydrocolloids, milk proteins, and other soluble substances. Insoluble particles, such as ice crystals, lactose crystals, and milk solids, are suspended in the aqueous phase. Dispersed milk fat globules are generating an emulsion in its aqueous phase as well (Sain et al. 2024; Susngi et al. 2019).

This frozen delicacy is unique because to the intricate interaction of ingredients and freezing dynamics, as well as the representation of a culinary heritage. The process of freezing has a crucial role in determining the crystalline structure and sensory characteristics of *kulfi*, hence impacting its overall quality (Assegehegn et al. 2019; Dalvi-Isfahan et al. 2019). The preservation of the creamy smoothness and tastes that characterize this cultural delicacy depends critically on exact control over the freezing conditions.

Beyond being aesthetically pleasing, knowing and anticipating freezing dynamics is critical when it comes to frozen sweets. It is essential for streamlining production procedures, guaranteeing consistency in product quality and raising manufacturing efficiency in the food industry as a whole (Bhagya Raj and Dash 2022). Predicting freezing temperatures is beneficial in many scenarios, as it gives the food business a scientific basis for resource management and process improvement (Ray et al. 2025).

When attempting to understand the complex interactions between factors impacting the freezing dynamics of food items, regression modelling proves to be a useful tool. It makes possible to investigate these factors methodically and offers quantitative insights into how they affect the freezing process (Quijano-Ortega et al. 2020; Lopez Quiroga et al. 2020). Regression modelling has been used in numerous studies on food products in recent years, including studies on how to improve food products' shelf lives (Wunderlich et al. 2023), how to study microbial growth (Aditama and Munir 2022), how to determine food's caloric content (Skjerdal et al. 2021), how to predict food prices (Wibowo and Yasmina, 2021) and how to characterize food products (Asnhari et al. 2019).

Even though regression modelling has been used in many studies in several areas of food science, there is still a significant study void in the particular area of *kulfi* freezing. Regression modelling has been used to better understand and improve a variety of food processes (Sain et al. 2023), but it hasn't been tested in the context of *kulfi* freezing.

This study bridges research gap by delving into the world of *kulfi* freezing through the lens of regression modelling. The objective was to create a reliable regression model that, using the temperature dynamics of *kulfi* samples as a basis, can forecast refrigerator air temperature with accuracy. By doing this, this study opens the door for advantageous uses in the food industry in addition to furthering our scientific understanding of the freezing processes involved in the production of frozen desserts.

This study contributes significantly to the scientific understanding of freezing processes in the realm of frozen desserts, specifically addressing the research gap in regression modelling for *kulfi* freezing dynamics. The developed prediction model not only enhances our understanding of *kulfi* production but also holds practical implications for optimizing freezing conditions, reducing resource consumption and ensuring consistent product quality in the food industry.

Materials and Methods

Kulfi mix preparation

The first stage in making *kulfi* was to heat milk to concentrate it by 50%. This was an important step since it allowed the *kulfi* to have the right texture and richness (Siva et al. 2019). The concentrated milk was then carefully mixed with 15% sugar and the mixture was agitated vigorously (Kedaree et al. 2021). In addition to making the *kulfi* more flavourful, sugar is essential for its general consistency and freezing qualities. Vigorous stirring guarantees that the sugar is distributed evenly throughout the mixture, which encourages homogeneity.

Experimental configuration of the trial

After the *kulfi* mix was carefully prepared, it was put into a 240 ml capacity *kulfi* mould. This mould was carefully constructed with four separate sections that held 60 ml of the *kulfi* mixture (Fig 1.). Separating the samples into four compartments made it easier to work with each one individually and also made it possible to conduct a methodical, controlled study of freezing dynamics. After the mould was carefully filled, the whole assembly was quickly put into a deep freezer cabinet to begin the freezing process (Solanki et al. 2023). To capture the temporal development of freezing features in each individual compartment, the *kulfi* samples were frozen for 200 minutes.

Temperature monitoring of the experimental trial

To record the temporal details in the experimental setup, a meticulous method was used in the context of temperature monitoring (Ray et al. 2024). To provide spatial granularity for temperature evaluation, four Pt100 sensors were positioned into each of the mould's four distinct *kulfi* chambers. To further track the total ambient temperature within the deep freezer cabinet, a fifth Pt100 sensor was positioned strategically in the freezer air duct. A data logger, a temperature monitoring device that can

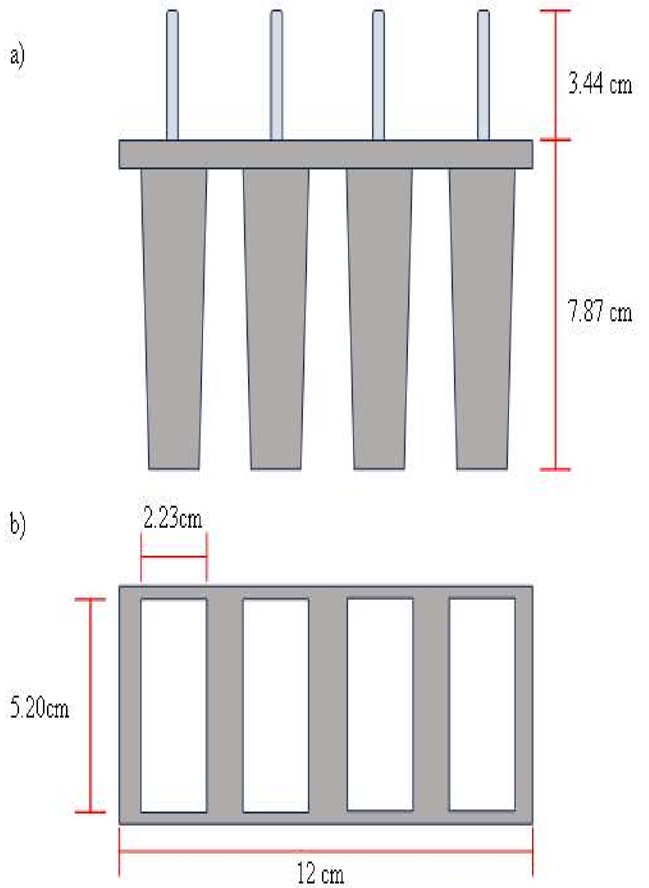

Fig. 1 Schematic diagram of the *kulfi* mould (a: Top view; b: Side view)

collect and store temperature data at one-minute intervals, was methodically linked to these sensors.

Analysis of all the various regression models

A thorough approach was conducted by taking into account 24 different regression models in an attempt to precisely estimate freezing air temperature based on product temperature throughout the *kulfi* freezing process (Table 1). A wide variety of models, including neural network, linear, tree-based, support vector machine (SVM) and gaussian process regression (GPR) models, were evaluated throughout the selection process. Each model provided a different perspective on the intricate interaction between the variables. After this thorough model analysis, the model with the highest performance was selected based on metrics like Mean Absolute Error (MAE), goodness of fit (R^2), root mean square error (RMSE) and mean squared error (MSE) (Chicco et al. 2021). After that, the chosen model was carefully fitted to the experimental data and trained in order to maximize its prediction power. A comprehensive examination of the actual and anticipated reactions was used to evaluate the appropriateness of the model, providing a detailed knowledge of how well the model matched the observed data (Chakraborty and Ghosh 2020). Comprehensive findings were produced and methodically examined in order to examine the model's performance in more depth.

Results and Discussion

Goodness of fit (R^2) analysis of all the various regression models

The linear model (Table 2) had a high R^2 value of 0.94, indicating that the linear connection with *kulfi* temperature could be responsible for a substantial amount of the fluctuation in freezer air temperature. With a systematic variable selection approach, the stepwise linear model had enhanced explanatory power, as shown by its R^2 of 0.96. Strong R^2 values of 0.96 and 0.97, respectively, were shown by tree-based models such Fine Tree and Boosted Trees, demonstrating their capacity to grasp intricate connections in the data. With an R^2 of 0.74, Coarse Tree trailed behind, suggesting possible issues with adequately fitting the data. R^2 values for SVM models ranged from 0.86 to 0.94, indicating consistent performance. Significantly, Cubic SVM displayed a negative R^2 value (-34.05), indicating an unsuitable model selection or a poor fit. The GPR models with R^2 values greater than 0.97 demonstrated outstanding fits. These models included Squared Exponential GPR, Metem 5/2 GPR, Exponential GPR and Rational Quadratic GPR. With an R^2 of 0.999, the Rational Quadratic GPR model showed complete agreement with the observed data. High R^2 values were shown by neural network models; the Trilayered Neural Network achieved 0.998, indicating a strong capacity to identify complex patterns in the data.

With a perfect match to the data, the Rational Quadratic GPR model was determined to be the best option based on the R^2 value (Sharma et al. 2019). Based on the *kulfi* sample temperature, this model could be considered the best regression model for predicting the freezer air temperature.

Root Mean Square Error (RMSE) analysis of all the various regression models

RMSE indicates (Table 2) that the linear model, which is defined by a clear link between the variables, has an RMSE of 1.67. The RMSE of 2.27 was slightly higher as a consequence of the interactions linear model, which included interactions between variables. With an RMSE of 1.43, the stepwise linear model which incorporates a methodical variable selection process exhibited potential. An RMSE of 2.07 was obtained using the robust linear model, which was intended to manage outliers. Fine Tree and Boosted Trees, two tree-based models, performed competitively with RMSE values of 1.37 and 1.21, respectively. On the other hand, the Coarse Tree had a larger RMSE of 3.55, suggesting that it could have overfitted or not fitted the data well enough. The accuracy of the linear and non-linear SVM models varied. Interestingly, Cubic SVM showed an RMSE of 41.35, which is very high and indicates a poor fit to the data. Competitive performance was shown by GPR models, particularly Squared Exponential GPR, Metem 5/2 GPR, Exponential GPR and Rational Quadratic GPR. Showcasing a 0.46 RMSE, the Rational Quadratic GPR turned out to be the best option. The performance of neural network models, which differ in their designs, varied. With an

Table 1 Different regression models considered for analysis

Sl. No.	Regression Model
1	Linear
2	Interactions Linear
3	Robust Linear
4	stepwise Linear
5	Fine Tree
6	Medium Tree
7	Coarse Tree
8	Linear Support Vector Machine
9	Quadratic Support Vector Machine
10	Cubic Support Vector Machine
11	Fine Gaussian Support Vector Machine
12	Medium Gaussian Support Vector Machine
13	Coarse Gaussian Support Vector Machine
14	Boosted Trees
15	Bagged Trees
16	Squared Exponential Gaussian Process Regression
17	Metem 5/2 Gaussian Process Regression
18	Exponential Gaussian Process Regression
19	Rational Quadratic Gaussian Process Regression
20	Narrow Neural Network
21	Medium Neural Network
22	Wide Neural Network
23	Bilayered Neural Network
24	Trilayered Neural Network

RMSE of 0.77, the Trilayered Neural Network was the most notable.

The Rational Quadratic GPR model showed better predicted accuracy based on the RMSE study, maybe because it was capable of capturing intricate non-linear interactions between the temperature of the *kulfi* sample and the freezer air. Analogously, researchers used this model for diverse objectives and discovered that it had strong predictive accuracy and dependability (Pandit and Infield 2019; Alnaqbi et al. 2023).

Mean Squared Error (MSE) analysis of all the various regression models

The linear model's MSE between the actual and projected freezer air temperatures were 2.78, as shown in Table 2. With a reduced MSE of 2.06, the stepwise linear model fared better than the linear model, demonstrating the value of methodical variable selection. Tree-based models performed competitively, with MSE values of 1.48 and 1.46 for Fine Tree and Boosted Trees, respectively. Nevertheless, Coarse Tree demonstrated a significantly elevated MSE of 12.68, suggesting possible difficulties in precisely forecasting freezer air temperature. The prediction accuracy of the SVM models varied, with Cubic SVM displaying an unusually high MSE of 1709.6. This anomaly points to a poor model fit or improper choice. Strong performance was shown by GPR models, such as Squared Exponential GPR, Metem 5/2 GPR, Exponential GPR and Rational Quadratic GPR. The low MSE of 0.21 for the Rational Quadratic GPR model suggests that it is a good fit for reducing prediction mistakes. Competitive MSE values were shown by neural network models, with the Trilayered Neural Network exhibiting the lowest MSE of 0.60. This implies that it can identify intricate patterns in the data, which improves prediction accuracy.

Among the regression models examined, the Rational Quadratic GPR model had the lowest MSE, making it the best option. The results highlight that the lowest MSE value of this model exhibited quantitative basis for evaluating the performance of predictive accuracy in freezing air temperature (Madhukumar et al. 2022).

Mean Absolute Error (MAE) analysis of all the various regression models

The linear model showed an average MAE of 1.17 between the actual and projected freezer air temperatures, as shown in Table 2. With a reduced MAE of 1.06, the stepwise linear model fared better than the linear model, highlighting the significance of methodical variable selection. Tree-based models with MAE values of 0.66 and 0.96, respectively, demonstrated competitive performance, as shown by Fine Tree and Boosted Trees. Coarse Tree, on the other hand, had a larger MAE of 2.7805, indicating difficulties in precisely estimating freezer air temperature. The predicted performance of the SVM models varied, with Cubic

Table 2: Goodness of fit (R^2), root mean square error (RMSE), mean squared error (MSE), and mean absolute error (MAE) values of all the 24 various regression models

Regression Model	RMSE	R^2	MSE	MAE
Linear	1.6682	0.94	2.7828	1.1711
Interactions Linear	2.2692	0.89	5.1491	1.0891
Robust Linear	2.0675	0.91	4.2744	1.2203
stepwise Linear	1.4342	0.96	2.057	1.0573
Fine Tree	1.3705	0.96	1.8784	0.66288
Medium Tree	1.9236	0.92	3.7004	1.3753
Coarse Tree	3.5469	0.74	12.68	2.7805
Linear SVM	1.7401	0.94	3.028	1.1233
Quadratic SVM	1.6859	0.94	2.8422	1.1767
Cubic SVM	41.347	-34.05	1709.6	14.193
Fine Gaussian SVM	1.3612	0.96	1.8529	1.0264
Medium Gaussian SVM	2.0618	0.91	4.251	1.4715
Coarse Gaussian SVM	2.6234	0.86	6.8823	2.0042
Boosted Trees	1.2103	0.97	1.4648	0.962
Bagged Trees	1.6053	0.95	2.577	1.0695
Squared Exponential GPR	1.1649	0.97	1.3571	0.4101
Metem 5/2 GPR	0.87275	0.98	0.76169	0.31908
Exponential GPR	0.46746	0.998	0.21852	0.22533
Rational Quadratic GPR	0.45837	0.999	0.21011	0.20403
Narrow Neural Network	1.2034	0.97	1.4482	0.73849
Medium Neural Network	0.88049	0.98	0.77526	0.59302
Wide Neural Network	0.92808	0.98	0.86134	0.55868
Bilayered Neural Network	0.90115	0.98	0.81207	0.56066
Trilayered Neural Network	0.77301	0.998	0.59754	0.45921

SVM displaying a high MAE of 14.19, suggesting possible limits in identifying the underlying patterns in the data. Strong performance was shown by GPR models, such as Squared Exponential GPR, Metem 5/2 GPR, Exponential GPR and Rational Quadratic GPR. The Rational Quadratic GPR model's ability to minimize absolute prediction errors is shown by its low MAE of 0.20. Competitive MAE values were shown by neural network models, with the Trilayered Neural Network exhibiting the lowest MAE of 0.46. This implies that it can identify intricate patterns in the data, which improves prediction accuracy.

The Rational Quadratic GPR model emerged as the optimal choice, exhibiting the lowest MAE among the regression models considered. The findings demonstrate that the low MAE values provided an accurate measure of the absolute prediction errors and gave insightful information about the model's performance in terms of its capacity to reduce differences between observed and projected values (Hacioðlu 2017).

Statistical comparison of the actual and predicted data by the selected model

The mean of the actual freezing air temperatures was -15.03°C, while the predicted mean was -15.05°C (Fig 2. and Fig 3.). This near alignment suggests that the data's central tendency was well captured by the Rational Quadratic GPR model (Olalusi and Awoyera 2021). Similar to this, there was excellent agreement in the median, which is the dataset's middle value. The projected median was -14.58°C, whereas the actual median was -14.4°C. The actual and anticipated data showed similar values for the data dispersion metrics, standard error and standard deviation. This implies that the variability seen in the freezing air temperature data was well reproduced by the Rational Quadratic GPR model. Understanding the distribution's shape was possible by looking at the skewness and kurtosis. The model seems to have caught

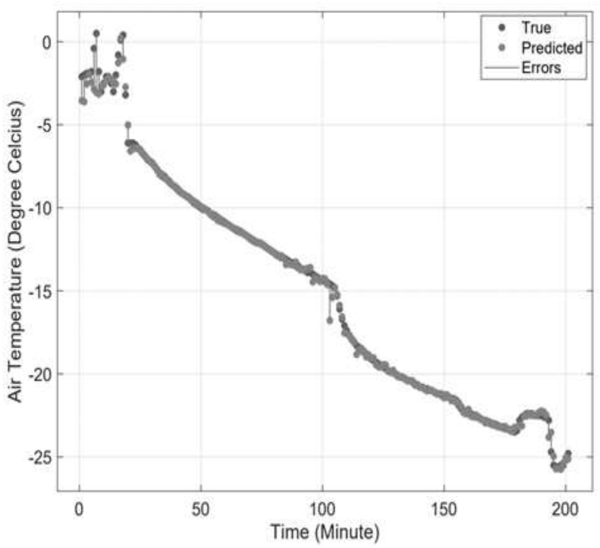

Fig 2. Response curve of the Rational Quadratic GPR model

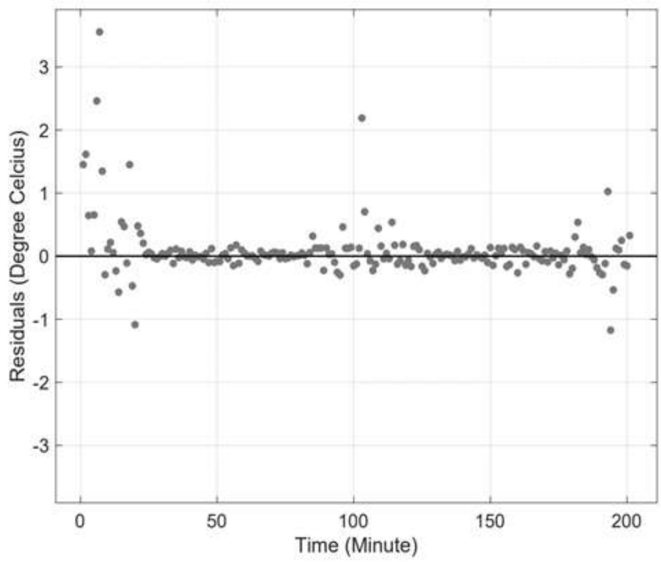

Fig 3. Actual vs predicted air temperature plot of the Rational Quadratic GPR model

the asymmetry and peakedness of the freezing air temperature distribution, based on the near values of kurtosis (-0.91°C for actual, -0.94°C for projected) and skewness (0.39°C for actual, 0.38°C for predicted) (Gundogdu and Guney 2007). The range, which denotes the variation between the highest and lowest values, exhibited a strong correlation between the real dataset (26.1°C) and the anticipated dataset (26.34°C). This suggests that the model successfully captured the distribution of below-freezing air temperatures. When examining individual data points, the real and projected dataset's lowest and maximum values nearly match, confirming the model's ability to represent extreme temperature values.

A significant degree of concordance between the actual and anticipated freezing air temperatures can be seen in the statistical comparison, demonstrating the effectiveness of the Rational Quadratic GPR model in simulating the main features of the observed temperature. In the setting of *kulfi* freezing, the model seems to have been robust and dependable in forecasting freezing air temperatures, as shown by the close agreement across many statistical indicators.

Analysis of residuals of the selected model

The analysis of residuals (Fig 4.), which represent the differences between the actual and predicted values in a regression model, provided valuable insights into the performance of the chosen Rational Quadratic GPR model. The residuals' mean, which was 0.02°C, indicates that the model, on average, underestimated the freezing air temperatures in *kulfi* freezing. The residuals' standard deviation and standard error, which represent the variability or dispersion of the prediction errors, were 0.33°C and 0.02°C, respectively. The low standard error indicates that the model's

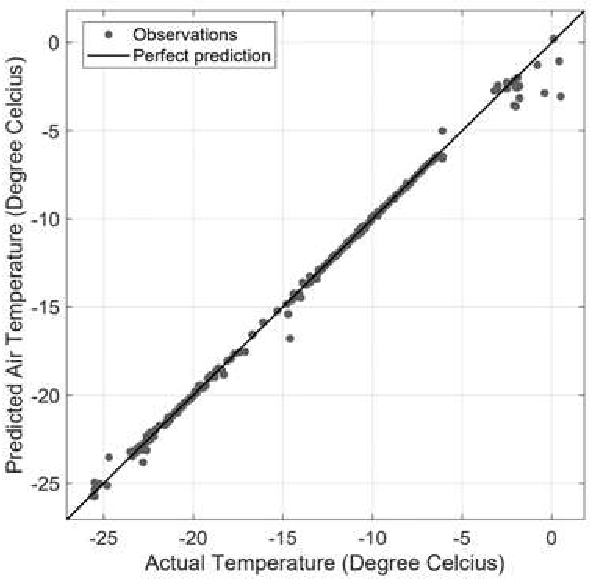

Fig 4. Residual plot of the Rational Quadratic GPR model

predictions were often in agreement with the observed data. The residuals were concentrated around the mean, as seen by the median of the residuals being very near to zero. The forecast errors showed considerable fluctuation, as seen by the range of 3.68°C, which represents the spread between the lowest and greatest residuals. The skewness of 3.22°C and kurtosis of 22.90°C suggest that the distribution of residuals was not entirely symmetrical and has heavier tails than a normal distribution. This suggests that the residuals could include a few outliers or very high or low values. The model sometimes overestimates and underestimates the freezing air temperatures, as shown by the lowest and highest residuals of -1.05! and 2.63!, respectively. An overall positive bias in the forecasts was shown by the positive sum of residuals (4.88°C). The absence of a mode suggests that there was no single value that appears more frequently in the residuals, indicating a relatively diverse distribution.

While the Rational Quadratic GPR model generally produced correct forecasts, the examination of residuals showed that there were times when it tended to overestimate or underestimate freezing air temperatures (Shen et al. 2017; Zhang et al. 2018). The skewness and kurtosis values suggested a departure from a perfectly normal distribution of residuals, indicating potential areas for improvement in the model.

Conclusions

This study explored the freezing dynamics of *kulfi* through the lens of regression modelling, aiming to develop a robust predictive model for refrigerator air temperature based on the temperature dynamics of *kulfi* samples. The Rational Quadratic Gaussian Process Regression model emerged as the optimal choice form all the other 23 regression models evaluated, showcasing superior performance across various evaluation metrics. The RMSE analysis highlighted the Rational Quadratic GPR model's (0.46) ability to capture complex non-linear relationships, demonstrating its superior predictive accuracy compared to other models. The goodness of fit value (0.999) reinforced the model's excellence, with a perfect fit observed. MSE (0.21) and MAE (0.20) analyses underscored the Rational Quadratic GPR model's effectiveness in minimizing prediction errors, providing a quantitative basis for evaluating its performance. Statistical comparison of actual and predicted data revealed a high level of concordance (Actual mean -15.03°C and predicted mean -15.05°C), affirming the model's robustness in reproducing key characteristics of freezing air temperatures. The analysis of residuals (Mean residual 0.02°C) showcased the model provided accurate predictions on average, there were instances of overestimation or underestimation. The departure from a perfectly normal distribution of residuals suggests potential areas for model improvement. In conclusion the adoption of the prediction model presents practical implications for optimizing kulfi freezing processes, ensuring precise control over refrigerator air temperatures to maintain product quality and consistency.

Acknowledgement

The authors are thankful to the Indian Council of Agricultural Research (ICAR) and National Dairy Research Institute, Karnal for providing the necessary facilities to conduct this study.

Funding

The study was financially supported by Indian Council of Agricultural Research (ICAR) and National Dairy Research Institute, Karnal

Conflicts of interest

The authors declare that they have no conflicts of interest.

References

Aditama N, Munir R (2022) Indonesian Street Food Calorie Estimation Using Mask R-CNN and Multiple Linear Regression. Proc 2022 2nd Int Conf Power Control Comput Technol (ICPC2T). pp 1–6

Alnaqbi AJ, Zeiada W, Al-Khateeb GG, Hamad K, Barakat S (2023) Creating Rutting Prediction Models through Machine Learning Techniques Utilizing the Long-Term Pavement Performance Database. Sustainability 15:13653

Asnhari SF, Gunawan PH, Rusmawati Y (2019) Predicting Staple Food Materials Price Using Multivariables Factors (Regression and Fourier Models with ARIMA). Proc 2019 7th Int Conf Inf Commun Technol (ICoICT). pp 1–5

Assegehegn G, Brito-de la Fuente E, Franco JM, Gallegos C (2019) The importance of understanding the freezing step and its impact on freeze-drying process performance. J Pharm Sci 108:1378–1395

Bhagya Raj GVS, Dash KK (2022) Comprehensive study on applications of artificial neural network in food process modeling. Crit Rev Food Sci Nutr 62:2756–2783. https://doi.org/10.1080/10408398.2020.1858398

Chakraborty T, Ghosh I (2020) Real-time forecasts and risk assessment of novel coronavirus (COVID-19) cases: A data-driven analysis. Chaos, Solitons & Fractals 135:109850

Chicco D, Warrens MJ, Jurman G (2021) The coefficient of determination R-squared is more informative than SMAPE, MAE, MAPE, MSE and RMSE in regression analysis evaluation. PeerJ Comput Sci 7:e623. https://doi.org/10.7717/peerj-cs.623

Dalvi-Isfahan M, Jha PK, Tavakoli J, Daraei-Garmakhany A, Xanthakis E, Le-Bail A (2019) Review on identification, underlying mechanisms and evaluation of freezing damage. J Food Process Engineering 255:50–60

Gundogdu KS, Guney I (2007) Spatial analyses of groundwater levels using universal kriging. J Earth Syst Sci 116:49–55. https://doi.org/10.1007/s12040-007-0006-6

Hacioðlu R (2017) Prediction of solar radiation based on machine learning methods. J Cogn Syst 2:16–20

Kedaree VC, Nalkar SD, Kekan AM (2021) Preparation of kulfi blended with guava (Psidium guajava) powder. J Pharmacogn Phytochem 10:474–478

Lopez Quiroga E, Prosapio V, Fryer PJ, Norton IT, Bakalis S (2020) Model discrimination for drying and rehydration kinetics of freeze dried tomatoes. J Food Process Engineering 43:e13192. https://doi.org/10.1111/jfpe.13192

Madhukumar M, Sebastian A, Liang X, Jamil M, Shabbir MNSK (2022) Regression model-based short-term load forecasting for university campus load. IEEE Access 10:8891–8905

Olalusi OB, Awoyera PO (2021) Shear capacity prediction of slender reinforced concrete structures with steel fibers using machine learning. Eng Struct 227:111470

Pandit RK, Infield D (2019) Comparative analysis of Gaussian process power curve models based on different stationary covariance functions for the purpose of improving model accuracy. Renew Energy 140:190–202

Quijano-Ortega N, Fuenmayor CA, Zuluaga-Dominguez C, Diaz-Moreno C, Ortiz-Grisales S, García-Mahecha M, Grassi S (2020) FTIR-ATR Spectroscopy Combined with Multivariate Regression Modeling as a Preliminary Approach for Carotenoids Determination in Cucurbita spp. Appl Sci 10:3722

Ray A, Minz PS, Sinha C (2024) Framework for accurate estimation of freezing time and convective heat transfer coefficient for freezing of a food product in domestic refrigerator: a numerical and simulation modeling approach. Multiscale and Multidiscip Model Exp and Des. https://doi.org/10.1007/s41939-024-00533-0

Ray A, Minz PS, Sinha C, John H (2025) Development and Investigation of a Novel Freezer Attachment for Rapid Freezing of Frozen Dairy Products. J Food Process Eng 48:e70202. https://doi.org/10.1111/jfpe.70202

Sain M, Minz P, Zade S, Ray A, John H, Kumar S, Gautam A, Berry S (2023) Assessing the effect of variation in fat content and temperature on the electrical conductivity of milk: A regression modelling approach. Ama, Agric Mech Asia Afr Lat Am

Sharma V, Dewangan HK, Maurya L, Vats K, Verma H (2019) Rational design and in-vivo estimation of Ivabradine Hydrochloride loaded nanoparticles for management of stable angina. J Drug Deliv Sci Technol 54:101337

Shen X, Li Q, Wu G, Zhu J (2017) Bias compensation for rational polynomial coefficients of high-resolution satellite imagery by local polynomial modeling. Remote Sens 9:200

Siva K, Das A, David J, Bharti BK, Kumar P, Shukla S (2019) Studies on characteristics of flaxseed powder supplemented Kulfi. Int J Chem Stud 7:924–928

Skjerdal T, Gangsei LE, Alvseike O, Kausrud K, De Cesare A, Alexa E-A, Alvarez-Ordóñez A, Moen LH, Osland AM, From C, Nordvik B, Lindbäck T, Kvello J, Folgerø B, Dommersnes S, Hauge SJ (2021) Development and validation of a regression model for Listeria monocytogenes growth in roast beefs. Food Microbiol 98:103770. https://doi.org/10.1016/j.fm.2021.103770

Solanki K, Rani R, Gaur G (2023) Development and Characterization of Herbal Kulfi (Ice Cream) Using Tulsi, Ginger, and Clove. Indian J Dairy Sci 76:1–7

Susngi SR, Das A, Dympep P, Gupta DK, Bharti BK, Ranvir SG, David J (2019) Studies on development of kulfi supplemented with peach pulp. J Pharmacogn Phytochem 8:985–988

Wibowo A, Yasmina I (2021) Food Price Prediction Using Time Series Linear Ridge Regression with the Best Damping Factor. Adv Sci Technol Eng Syst J 6:694–698

Wunderlich P, Pauli D, Neumaier M, Wisser S, Danneel H-J, Lohweg V, Dörksen H (2023) Enhancing Shelf Life Prediction of Fresh Pizza with Regression Models and Low Cost Sensors. Foods 12:1347. https://doi.org/10.3390/foods12061347

Zhang N, Xiong J, Zhong J, Leatham K (2018) Gaussian process regression method for classification for high-dimensional data with limited samples. Proc 2018 8th Int Conf Inf Sci Technol (ICIST). IEEE, pp 358–363