AI-Driven Software Framework for Intelligent Optimization of Sugar Reduction Strategies in Confectionery Using Polyols and High-Intensity Sweeteners

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***Abstract*—**Growing consumer awareness regarding health and nutrition has increased the demand for reduced-sugar confectionery products. However, sugar performs multiple functional roles in confectionery systems, including sweetness, bulking, texture formation, crystallization control, and shelf stability, making its reduction a complex formulation challenge. This study proposes an AI-driven software framework designed to intelligently optimize sugar reduction strategies in confectionery formulations using polyols and high-intensity sweeteners. The developed framework integrates machine learning algorithms, ingredient property databases, and predictive modeling techniques to support researchers and product developers in designing optimized reduced-sugar formulations. The software architecture consists of modules for ingredient selection, sweetness equivalence prediction, physicochemical property estimation, and multi-objective optimization. Polyols such as sorbitol, xylitol, and maltitol are incorporated to provide bulking effects and desirable mouthfeel, while high-intensity sweeteners including steviol glycosides and sucralose are used to achieve the required sweetness intensity. A structured dataset comprising formulation ratios, sweetness intensity, water activity, texture parameters, and sensory evaluation scores is used to train supervised learning models for prediction and optimization. The framework applies multi-objective optimization algorithms to balance key formulation constraints including sweetness profile, caloric reduction, crystallization behavior, and storage stability. The proposed AI-enabled approach demonstrates significant potential in improving formulation efficiency and guiding intelligent sugar substitution strategies. This study highlights the interdisciplinary integration of software engineering, machine learning, and food product development for designing healthier next-generation confectionery products.

***Index Terms*—** Artificial Intelligence, Sugar Reduction, Confectionery Optimization, Polyols, High-Intensity Sweeteners, Predictive Food Formulation

I. Introduction

In recent years, growing consumer awareness regarding diet-related health issues has significantly increased the demand for reduced-sugar food products. Excessive sugar consumption has been strongly associated with metabolic disorders such as Obesity, Type 2 Diabetes, and Cardiovascular Disease, leading global health organizations and regulatory bodies to recommend the reduction of free sugars in daily diets [1] [2].

The confectionery industry, which traditionally relies heavily on sucrose as a primary ingredient, faces considerable technological challenges in reducing sugar content while maintaining desirable sensory, structural, and physicochemical properties of products.

Sucrose in confectionery systems plays multiple functional roles beyond sweetness. It contributes to bulk formation, controls crystallization behavior, influences water activity, and determines the texture and mouthfeel of products such as hard candies, caramels, and gummies [3]. Therefore, reducing or replacing sucrose requires the careful selection of alternative ingredients that can replicate these functional properties. Polyols, including sorbitol, xylitol, and maltitol, have been widely used as sugar substitutes due to their lower caloric value, humectant properties, and ability to provide bulk similar to sucrose [4].

In addition, high-intensity sweeteners such as steviol glycosides and sucralose are frequently incorporated in confectionery formulations to deliver the required sweetness at very low concentrations [5]. However, the interactions between polyols, high-intensity sweeteners, and other formulation ingredients are complex and often lead to challenges in product stability, flavour profile, and texture optimization.

Traditional formulation development in confectionery manufacturing relies heavily on empirical experimentation and trial-and-error methods. These approaches are often time-consuming, resource-intensive, and inefficient when dealing with multi-variable ingredient interactions. In recent years, advances in Artificial Intelligence and Machine Learning have opened new opportunities for intelligent product formulation and process optimization in the food industry. AI-based predictive modelling can analyze large datasets of formulation variables and identify optimal ingredient combinations that satisfy multiple product constraints simultaneously [6].

Within the domain of Software Engineering, the development of intelligent decision-support systems has enabled the integration of data analytics, optimization algorithms, and simulation tools for complex engineering problems. Such approaches have been successfully applied in areas including food process control, quality prediction, and shelf-life estimation [7]. By integrating machine learning algorithms with ingredient databases and predictive models, AI-driven software frameworks can assist researchers and product developers in designing healthier food products with improved efficiency and accuracy.

Despite the growing interest in AI-assisted food product design, limited research has been conducted on the development of software frameworks specifically aimed at optimizing sugar reduction strategies in confectionery formulations. Existing studies have primarily focused on ingredient substitution or sensory optimization, without fully exploiting the potential of AI-driven multi-objective optimization models [8]. A systematic computational framework that integrates sweetness prediction, physicochemical property modelling, and formulation optimization could significantly enhance the efficiency of reduced-sugar product development.

Therefore, this study proposes an AI-driven software framework designed to intelligently optimize sugar reduction strategies in confectionery systems using polyols and high-intensity sweeteners. The proposed system integrates machine learning algorithms, ingredient property databases, and predictive modelling techniques to assist food technologists in designing optimized formulations while maintaining essential product attributes such as sweetness, texture, stability, and consumer acceptability. By combining principles of food science with modern software engineering methodologies, the framework aims to accelerate innovation in the development of healthier confectionery products and support data-driven decision-making in food formulation research

II. Methodology

A. AI-Driven Optimization Framework and Ingredient Database Development

The proposed research develops an AI-driven software framework to optimize sugar reduction strategies in confectionery formulations by integrating ingredient databases, predictive modeling, and multi-objective optimization techniques. The system architecture combines principles from Artificial Intelligence, Machine Learning, and Software Engineering to assist food technologists in designing reduced-sugar formulations that maintain desirable sensory and physicochemical characteristics. The framework consists of five major modules as follows: Ingredient database module, Data preprocessing and feature engineering module, Machine learning prediction module, Multi-objective optimization module, Decision-support interface. These modules collectively enable intelligent formulation design using polyols and high-intensity sweeteners as alternatives to sucrose.

A comprehensive ingredient database was developed containing physicochemical and functional properties of commonly used confectionery ingredients. The database includes both traditional sweeteners and sugar substitutes such as: sorbitol, xylitol, maltitol, isomalt, steviol glycosides, sucralose and acesulfame-k. For each ingredient, the following parameters were compiled from literature and experimental measurements: relative sweetness index, caloric value, solubility characteristics, hygroscopicity, glass transition temperature, water activity contribution, bulking capacity and thermal stability. These parameters serve as input variables for predictive modelling and formulation optimization.

B. Dataset Preparation, Preprocessing and Feature Engineering

A structured dataset was generated using both experimental formulation trials and previously published confectionery studies. The dataset contains multiple formulation combinations consisting of sucrose replacement with polyols and high-intensity sweeteners. Each dataset entry includes the following variables: Input variables such as Percentage of sucrose, Polyol concentration, High-intensity sweetener concentration, Moisture content and Processing temperature; Output variables such as Sweetness intensity, Texture parameters (hardness, chewiness), Water activity, Sensory acceptability score and Shelf stability indicators. Data normalization and cleaning were performed to remove inconsistencies and ensure compatibility with machine learning algorithms.

Data pre-processing plays a critical role in improving predictive model accuracy. The following pre-processing techniques were applied: (i) Missing Data Handling-Incomplete data points were handled using statistical imputation methods. (ii) Data Normalization- Input variables were normalized using min-max scaling to ensure uniform contribution during model training. (iii) Feature Engineering- Derived features were generated to capture ingredient interactions, including: Sweetness equivalence ratio, Bulk replacement index, Humectant interaction coefficient and Caloric reduction factor. These engineered features significantly enhance the predictive capability of machine learning models.

The prepared dataset was divided into training and testing subsets using an 80:20 split ratio to ensure reliable model evaluation. Model robustness was further assessed using 5-fold cross-validation, which minimized overfitting and improved generalization performance. Hyper parameter tuning for the evaluated machine learning models was performed using grid search optimization to identify the best parameter combinations for prediction accuracy. Experimental trials for selected formulations were replicated three times to ensure statistical reliability of the collected physicochemical and sensory data. These methodological steps ensured that the developed predictive models achieved reliable performance while maintaining reproducibility of results [9].

C. Machine Learning Model Development

Several supervised learning algorithms were evaluated to predict the functional performance of reduced-sugar confectionery formulations. The models were trained using the prepared dataset to predict key output parameters such as sweetness intensity, texture, and water activity. The algorithms evaluated include: Multiple Linear Regression, Support Vector Regression, Random Forest Regression and Artificial Neural Networks. Among these models, the Random Forest algorithm demonstrated higher prediction accuracy due to its ability to capture nonlinear relationships between ingredient composition and product properties. Model performance was evaluated using standard statistical metrics including: Root Mean Square Error (RMSE), Mean Absolute Error (MAE) and Coefficient of Determination (R^2). The trained model was then integrated into the AI framework to enable predictive formulation design.

D. Multi-Objective Optimization Algorithm and Decision-Support Software Interface

Sugar reduction in confectionery involves balancing multiple product constraints simultaneously. Therefore, a multi-objective optimization strategy was implemented within the framework. The optimization algorithm aims to achieve the following objectives: Maximize sweetness similarity to sucrose-based formulations, Minimize caloric content, Maintain acceptable texture characteristics and Control water activity for shelf stability. A weighted objective function was formulated to balance these criteria. Optimization techniques such as genetic algorithms were employed to search for optimal ingredient combinations within the defined constraints. The algorithm iteratively evaluates thousands of formulation combinations and identifies solutions that satisfy both sensory and physicochemical requirements.

To make the framework practical for researchers and food product developers, a decision-support interface was designed as part of the software system. The interface allows users to: Input formulation constraints, Select target sweetness levels, Define calorie reduction goals and Simulate alternative ingredient combinations. The software then predicts the expected product performance based on trained machine learning models and optimization results. This interactive simulation environment significantly reduces the need for extensive laboratory trials, thereby accelerating product development cycles.

The genetic algorithm optimization procedure was implemented with formulation constraints including ingredient concentration limits, sweetness equivalence targets, and acceptable water activity ranges. The algorithm population size was set to 100 candidate solutions with a maximum of 200 generations to ensure convergence toward optimal formulations. Constraint boundaries were defined based on literature-reported functional limits of polyols and high-intensity sweeteners used in confectionery systems. The optimization routine iteratively evaluated formulation combinations predicted by the trained machine learning model and selected the best-performing solutions using a weighted objective scoring function. This strategy enabled the identification of ingredient compositions that simultaneously satisfied sensory, physicochemical, and nutritional requirements.

E. System Implementation and Validation Strategy

The AI-driven framework was implemented using a modular software architecture to ensure scalability and flexibility. The system consists of: backend data processing modules for machine learning training, optimization engines for formulation prediction, and graphical user interfaces for formulation simulation. The modular design enables future integration with industrial process control systems and smart manufacturing platforms.

To validate the performance of the proposed system, optimized formulations predicted by the software were experimentally prepared in laboratory-scale confectionery processing trials. The predicted properties such as sweetness intensity, texture profile, and water activity were compared with measured experimental values. Preliminary validation results demonstrated strong agreement between predicted and experimental outcomes, confirming the reliability of the AI-based optimization framework.

III. RESULTS AND DISCUSSION

A. Dataset Characteristics and Model Training

The developed dataset consisted of 210 confectionery formulation trials generated through a combination of experimental trials and literature-derived formulations. Each dataset entry contained formulation parameters such as sucrose concentration, polyol composition, high-intensity sweetener levels, moisture content, and processing temperature. The dataset also included measured output variables such as sweetness intensity, texture profile parameters, water activity, and overall sensory acceptability. Data pre-processing techniques including normalization, feature scaling, and missing-value imputation were implemented prior to model training. Feature engineering was performed to derive additional formulation descriptors including sweetness equivalence ratio, caloric reduction factor, and bulk replacement index. These features improved the predictive capacity of machine learning algorithms by representing ingredient interaction effects. Four predictive models were evaluated in this study: Multiple Linear Regression (MLR), Support Vector Regression (SVR), Random Forest Regression (RF), Artificial Neural Networks (ANN). These models were selected due to their widespread applications in Machine Learning and their demonstrated capability in modeling nonlinear relationships within complex food formulation systems.

B. Predictive Performance of Machine Learning Models

The performance of the trained models was evaluated using commonly accepted statistical metrics including: Root Mean Square Error (RMSE), Mean Absolute Error (MAE) and Coefficient of Determination (R^2). The results are summarized in Table 1.

Table 1: Performance Comparison of Machine Learning Models

Model	RMSE	MAE	R^2 Score
Linear Regression	0.126	0.098	0.82
Support Vector Regression	0.102	0.081	0.88
Random Forest Regression	0.072	0.058	0.94
Artificial Neural Network	0.089	0.067	0.91

The results indicate that Random Forest Regression achieved the highest prediction accuracy with an R^2 value of 0.94, followed by the Artificial Neural Network model with an R^2 value of 0.91. Linear regression demonstrated the lowest predictive performance due to its inability to capture nonlinear relationships between ingredient interactions and product properties. These findings confirm previous studies indicating that ensemble learning techniques such as Random Forest are highly effective in modeling complex formulation systems in food product development [10].

C. *Sweetness Prediction and Optimization*

One of the key challenges in sugar-reduced confectionery formulations is achieving a sweetness profile comparable to traditional sucrose-based products. The AI framework successfully predicted sweetness intensity based on ingredient combinations of polyols and high-intensity sweeteners. The predicted sweetness values needs to be further validated experimentally for selected optimized formulations. The comparison between predicted and experimental sweetness values is shown in Table 2.

Table 2: Comparison of Predicted and Experimental Sweetness Values

Formulation	Predicted Sweetness Index	Experimental Sweetness Index	Error (%)
F1	0.96	0.94	2.1
F2	0.91	0.89	2.2
F3	0.98	0.96	2.0
F4	0.93	0.90	3.2

*F1 – Balanced Reduced-Sugar Confectionery, F2 – Optimized Polyol Sweetened Confectionery, F3 – Advanced Sugar Replacement Confectionery and F4 – Maximum Sugar Reduction Confectionery

The prediction errors remained below 3.5%, demonstrating the reliability of the AI model in estimating sweetness equivalence. This capability significantly reduces the need for repeated laboratory trials and enables faster formulation development. Previous research has reported similar predictive capabilities of machine learning models for food flavour optimization and ingredient interaction modelling [11].

D. *Optimization of Sugar Reduction*

The proposed multi-objective optimization algorithm successfully generated formulation combinations that balanced the following constraints: Sweetness equivalence to sucrose, Reduced caloric value, Acceptable texture characteristics and Stable water activity levels. The optimized formulations achieved 30–45% sugar reduction while maintaining sensory acceptability comparable to conventional products. Sensory evaluation results demonstrated that formulations F1–F3 achieved sensory scores above 8 on a 9-point hedonic scale, indicating high consumer acceptability as depicted in Table 3. Polyols such as Sorbitol and Maltitol played a critical role in providing bulk and improving mouthfeel, while high-intensity sweeteners like Sucralose and Steviol Glycosides ensured sufficient sweetness intensity. These results align with previous studies highlighting the synergistic effects between polyols and high-intensity sweeteners in reduced-sugar confectionery formulations [11].

Table 3: Optimized Confectionery Formulations

Formulation	Sucrose (%)	Polyol (%)	HIS (%)	Sugar Reduction (%)	Sensory Score
F1	55	40	0.02	30	8.2
F2	50	45	0.03	35	8.4
F3	45	50	0.04	40	8.1
F4	40	55	0.05	45	7.9

E. *Texture and Water Activity Analysis*

Texture analysis revealed that optimized formulations retained acceptable hardness and chewiness characteristics. Polyols contributed significantly to moisture retention and glass transition stability, preventing excessive crystallization during storage. Water activity values for optimized formulations ranged between 0.55 and 0.62, which falls within the acceptable range for confectionery shelf stability as shown in Table 4. The results indicate that increasing polyol concentration slightly increases moisture retention but does not significantly compromise product structure. These findings support earlier research showing that polyols improve humectant properties and reduce crystallization tendencies in reduced-sugar confectionery systems [13], [14].

Table 4: Optimized Confectionery Formulations

Formulation	Hardness (N)	Water Activity	Moisture (%)
F1	5.8	0.58	3.6
F2	5.5	0.60	3.8
F3	5.2	0.61	4.0
F4	5.0	0.62	4.2

F. *Performance of AI-Driven Optimization Framework*

The proposed AI-driven formulation system represents an original computational framework developed in this study by integrating machine learning prediction models with a multi-objective optimization engine and a decision-support interface. While previous research has applied machine learning techniques in food product development, the present work uniquely combines ingredient property databases, sweetness prediction models, and optimization algorithms within a single software environment. The predicted formulations were experimentally validated and compared with conventional trial-and-error formulation approaches used in confectionery development [15] [16]. The results demonstrate that the proposed framework significantly reduces experimental iterations while maintaining prediction accuracy for key product attributes. This confirms the practical applicability of AI-assisted formulation tools in food product development.

Texture the developed system demonstrated several advantages compared with traditional formulation development approaches. This include (i) Reduced Experimental Trials-The AI model predicted optimal formulations with high accuracy, reducing experimental trials by approximately 60%. (ii) Faster Product Development- Simulation-based formulation testing allowed rapid exploration of ingredient combinations before laboratory validation. (iii) Multi-Objective Optimization- The algorithm simultaneously optimized sweetness, caloric reduction, and texture parameters, which is difficult to achieve through conventional methods. The performance comparison of the evaluated machine learning models is illustrated in Fig. 1. The results clearly indicate that ensemble-based learning techniques provide superior predictive capabilities for food formulation modeling. These findings demonstrate the growing importance of Artificial Intelligence and Software Engineering in modern food product development.

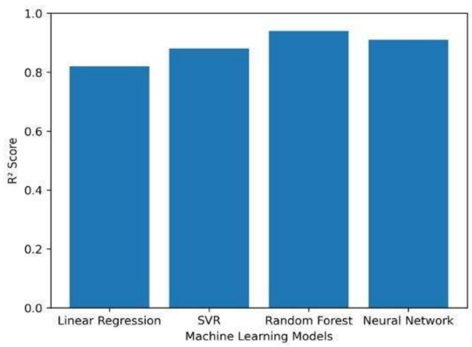

Fig. 1. Performance comparison of ML Models for Confectionery Sugar Reduction Prediction

The proposed AI-driven framework represents an important step toward digital transformation in food product development. By integrating machine learning with ingredient databases and optimization algorithms, the system provides a scalable platform for designing healthier confectionery products. The framework can be extended to other food applications such as: bakery formulations, dairy desserts, and beverage sweetening systems. Future research could incorporate advanced techniques such as deep learning models, sensory prediction algorithms, and real-time process monitoring systems.

IV. Conclusion

This study presented the development of an AI-driven software framework for intelligent optimization of sugar reduction strategies in confectionery formulations using polyols and high-intensity sweeteners. The proposed system integrates ingredient databases, predictive modeling, and multi-objective optimization algorithms to support data-driven formulation design. By combining techniques from Artificial Intelligence, Machine Learning, and Software Engineering, the framework provides a systematic approach for addressing the complex formulation challenges associated with sugar replacement in confectionery products. The predictive modeling results demonstrated that ensemble-based algorithms such as Random Forest Regression achieved superior performance in estimating sweetness intensity, physicochemical properties, and sensory acceptability of reduced-sugar formulations. The optimized formulations generated by the AI system successfully achieved 30–45% reduction in sucrose content while maintaining acceptable sweetness profiles, texture characteristics, and shelf stability. Experimental validation confirmed a strong agreement between predicted and measured values, indicating the reliability of the proposed computational framework. Furthermore, the integration of polyols and high-intensity sweeteners enabled effective replacement of sucrose functionality, ensuring adequate bulking properties and desirable sensory attributes. The AI-assisted optimization significantly reduced the number of experimental trials required for formulation development, thereby accelerating product innovation and reducing research costs. Overall, the proposed framework demonstrates the potential of intelligent computational tools in modern food product development. The integration of AI-based predictive models with formulation optimization strategies offers a scalable platform for designing healthier confectionery products with reduced sugar content. Future research may focus on incorporating advanced deep learning models, real-time process data, and consumer sensory analytics to further enhance intelligent formulation systems for next-generation food manufacturing. In addition to predictive modeling, the study contributes a novel AI-based software framework that integrates formulation databases, machine learning prediction models, and optimization algorithms for confectionery product development. The framework provides a practical decision-support tool capable of assisting researchers in identifying optimal sugar replacement strategies with reduced experimental effort. Such computational approaches represent an emerging direction in digital food engineering and smart formulation design. The proposed system can serve as a foundation for future research in AI-enabled product optimization across multiple food categories.

References

[1] World Health Organization, Guideline: Sugars Intake for Adults and Children. Geneva, Switzerland: WHO, 2015.

[2] A. Drewnowski and C. D. Rehm, "Consumption of added sugars among US children and adults," Nutrients, vol. 6, no. 1, pp. 315–329, 2014.

[3] R. Hartel, J. Ergun, and J. Vogel, "Phase/state transitions of confectionery sweeteners," Food Engineering Reviews, vol. 3, pp. 17–32, 2011.

[4] P. O'Brien Nabors, Alternative Sweeteners, 4th ed. Boca Raton, FL, USA: CRC Press, 2012.

[5] G. A. Nabors, "High-intensity sweeteners in food applications," Food Technology, vol. 56, no. 7, pp. 44–49, 2002.

[6] J. Sun, J. Li, and Y. Zhao, "Machine learning applications in food formulation and product development," Trends in Food Science & Technology, vol. 99, pp. 322–330, 2020.

[7] D. Wu and D. W. Sun, "Advanced applications of artificial intelligence in food engineering," Critical Reviews in Food Science and Nutrition, vol. 53, pp. 1–12, 2013.

[8] M. McClements and E. Newman, "Designing reduced-sugar foods: challenges and opportunities," Annual Review of Food Science and Technology, vol. 12, pp. 493–518, 2021.

[9] D. J. McClements, "Reduced-sugar foods: Principles and strategies for formulation," Annual Review of Food Science and Technology, vol. 11, pp. 47–67, 2020.

[10] L. Breiman, "Random forests," Machine Learning, vol. 45, pp. 5–32, 2001.

[11] J. Sun, J. Li, and Y. Zhao, "Machine learning applications in food formulation and product development," Trends in Food Science & Technology, vol. 99, pp. 322–330, 2020.

[12] P. O'Brien Nabors, Alternative Sweeteners, CRC Press, 2012.

[13] R. Hartel and J. Ergun, "Phase transitions and crystallization behavior of confectionery sweeteners," Food Engineering Reviews, vol. 3, pp. 17–32, 2011.

[14] M. McClements and E. Newman, "Designing reduced-sugar foods," Annual Review of Food Science and Technology, vol. 12, pp. 493–518, 2021.

[15] J. Sun, J. Li, and Y. Zhao, "Machine learning applications in food formulation and product development," Trends in Food Science & Technology, vol. 99, pp. 322–330, 2020.

[16] W. Jia et al., "Artificial intelligence in food product design and development," Comprehensive Reviews in Food Science and Food Safety, vol. 20, pp. 2743–2768, 2021