FreshSense: AI-Powered Shelf Life Optimization and Waste Reduction

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ABSTRACT

An industry that deals with food products, which have a very short shelf life, has undergone a number of obstacles including quality concerns, lack of revenue or even increased pollution. Most of the times, in cases where tra iditional syste ms are applied, the already existing systems lack mechanisms which can anticipate potential threats and outline steps to control them beforehand, and therefore lots of food is wasted along the food value chain [1]. To this end, the practical contribution of this paper is proposing a novel designed system intended to reduce the losses and waste of food through the use of artificial intelligence (AI) inter -net of things (IoT) and neural networks. The system manages to prolong shelf life of food products, storage of the product as well as enhance food quality through embedded AI models that predict food spoiling times [2]. It can be observed that the Fresh Sense gains the potential of the Internet of Things by enabling a constant flow of information and adeptly links the distribution of the products to the geography of consumption for the purpose of benefiting the supply chain [3]. As per the tests performed, the FreshSensors system can assist the enhancement of the shelf -life of these types of goods, where almost 28% is achieved, help to diminish the losses from spoilage by 40%, and help to restore 25% of the networks towards the efficiency of perishable supply chain management [4]. It is not only focusing on processes in real time but also includes artificial intelligence to the solutions of FreshSense that makes it applicable in the management of food resources in the circular economy and also enables to envision a sophisticated solution which aims at restriction of food loss in the perishable sector [5].

Keywords

Effective handling of perishable commodities, technological intervention towards food waste reduction, estimation of marketability period, intelligent surveillance, efficient surplus food reallocation, prediction data analysis, relevance of ai in food supply chain management, circular economy principles in food systems, interaction of food systems with environmental factors, and storage at a dynamic pace.

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1. INTRODUCTION

1.1 Background and Motivation

The global epidemic of food waste has also social, economic and environmental dimensions that can be compared to the drought, loss of food and even economic degradation. According to publication of Food and Agriculture Organization of the United Nations (FAO), more than one-third of food produced in one year is wasted totaling to 1.3 billion tones of food [2], [8]. This is wasteful and unnecessary, worse than half of the world's population 8% of the CO2 that is released into the environment comes from this problem which contributed to the climate change [6]. A significant amount of this waste is made up of easily perishable commodities such as fresh fruits, vegetables, dairy, and meat [14], [15]. It's no secret that the low movement performance of these categories of goods is associated with available distribution tools – shipping artillery, return shipping and, most importantly, predictive artillery which can put this concept in reverse all collide in order to create a decisive effect to these goods even before they reach their targeted consumers [7],[19]. Means of measuring the extent of resource mismanagement and over-exploitation are still not available [5], [12]. The systems in place are usually remedial in the sense that spoilage of goods is allowed but assurance of their quality comes after the event. These strategies aimed at correcting errors fail to reduce losses since they are built on the premise that changes will only come into effect after the storage or redistribution plan goes into action [10], [13]. Except for traditional food holding devices, smart technologies such as predictive analytics and real-time monitoring of food items which would help to control shelf life limiting factors are not incorporated in conventional food preservation systems [11],[18].

1.2 Problem Statement

Taking into consideration the need for a more effective and scientifically based policy when dealing with the determination of shelf life, waste management and surplus food control, the perishable food sector is very dynamic [5, 8]. Existing Technologies are not able to give a thorough and accurate forecasting of the wastes produced or clear up the waiting room using the inbuilt thermometer without an external device [16, 19]. Thus, food is lost even before its sell by date and that time for distribution is gone [2]. In such a way, the specific methodology has to be developed in order to seek the answers to these challenges:

Enhance the precision of the shelf life prediction: Such shelf life predictions implemented with machine learning enhancement is focused on the historical data of wastages and the weather outside [15, 17].

Connected sensors in a confined area: A real-time data transmission system as explained in [3],[18] can be used to alter the storage that fulfills the conditions { (temperature, humidity, illumination } to minimize loss of the contents.

1.3 Research Objectives

This study's main focus is the designing and implementation of a novel AI solutions known as FreshSense which applies machine learning, IOT and predictive technology to solve the problem of food wastage which has been talked about earlier [11], [17]. The end goal of FreshSense is to reduce waste produced in food business and promote the principle of sustainability in businesses [12], [13]. Among these, the following objectives can also be pointed out:

Enhancing the longevity predicting models: implementation of ratings predicting method based on machine learning/ self engineering/ self attending mechanisms in very short regular time spans together with foreign, domestic and multivariate time series predictions of failures in geographies [5], [16].

Storage Optimization System: it is a system that integrates searching networks and information processing systems carrying out operations on the environment related to the consumer in order to provide mission critical warnings that are time bound and reduce cargo spoilage while in transit [9], [18].

1.4 Contributions of This Work

FreshSense represents a new approach to food spoilage management by combining AI and IoT in an integrated system designed to predict spoilage, improve storage, and simplify food distribution [6], [10]. This work makes three key contributions

New life expectancy models: FreshSense integrates LSTM in a unified approach with modeling methods such as random forests, complementing the prediction based on the original model [17], [18]. This model can be adapted to different perishability factors to ensure prediction accuracy for different types of perishable products [1], [2].

Dynamic management of storage conditions: The system continuously adjusts storage settings to extend shelf life, ensuring timely redistribution to food banks [3], [19].

Innovation in reducing food waste: FreshSense exemplifies future innovations to reduce food waste and strengthen the circular economy [14], [16].]

2. LITERATURE REVIEW

2.1 The Global Food Waste Challenge and the Role of Circular Economy Models

Waste is a global problem and primarily affects food security, the economy, and the environment [2], [8]. The Food and Agriculture Organization of the United Nations (FAO) estimates that about a third of the food available for human consumption (about 1.3 billion tons per year) is lost or wasted [6], [14]. This waste costs about $940 million but accounts for about 8% of climate change [3], [8]. This waste includes fruits and vegetables, some dairy products, and some meat products that cannot be donated for fear of spoilage due to their perishability and environmental constraints [10], [12]. Circular economy models can effectively address the above challenges. They promote efficiency in resource use and eliminate waste from the production process to the final consumption stage [13], [15]. There is evidence that a circular economy can increase productivity, improve product clarity, and enhance the quality of food products [5], [14]. However, there are challenges in the business cycle, particularly in terms of damage control, maintenance, forecasting, and modeling of equipment ownership [7], [16]. Control shelf life, store, and recycle leftovers to minimize food waste. FreshSense offers a cleaner solution to contaminated food, addressing the shortcomings of previous commercial concepts and offering a practical, plant-based solution not yet available on the market [1], [20].

2.2 Machine Learning for Shelf Life Prediction of Perishable Foods

It is essential to know the shelf life of the different perishable goods in order to cut down on food wastage. Thereafter, the Random Forests, Support Vector Machines (SVM), and linear regression Approaches have been used more or less successfully to ahsort these Parameters types Temperature, Soil moisture, Microbical, as damages. These models are relevant and useful but also touch the issues of the Relevant Degree of Damage causing various kinds of damages. Nevertheless, their application is frequently constrained by the available information and the fact that consumables have a limit in timing factor. Such long-term perspective has been proved to be quite useful not so much in differentiating between values of stock but in managing inventory of perishable goods during some seasons effectively. For instance, FB Prophet is a time series forecasting tool that is set to rock the market by portraying a dimension of data-collected characteristics inter-relating with seasons and holidays. It was also established that food delivery service promotion can adopt FB Prophet because it offers seasonality and preference of different customers. Similarly, Xgboost is a machine learning technique that works by formulating and combining various models for particular purposes, it is particularly effective in cases where both explanatory and predictive capacities of the models are essential. XGBoost enhances the management of the modules enabling the focus to be on the damage-related modules only and assists other decision-making users in optimizing the hold strategies.

2.3 IoT for Real-Time Monitoring and Storage Optimization

The Internet of Things is used to monitor and store high-quality continuous information about the environment, such as temperature, humidity, and light [4], [19]. From sensors to smart warehouses, IoT devices can monitor events and send data for analysis to quickly detect and prevent corruption risks [2], [6]. Research shows that one of the main ways IoT can be used to improve the maintenance process is to increase the accuracy of maintenance, thereby reducing the damage that can be caused immediately by maintenance [13], [14]. Secure cloud storage using blockchain technology is one of the most popular methods today, but it can sometimes be expensive [12], [17]. Challenges include data integration and budgeting issues. Sensor calibration and data accuracy are two foundations of vibration testing because measuring environmental differences cannot cause damage [8], [18]. The ability of these tools to generate large amounts of information requires processing the information and solving problems with the appropriate resources [5], [15]. Therefore, platforms that can continuously manage the data and interpret it appropriately are needed. Everything depends on the platform, which uses IoT sensors that constantly measure the environment to send notifications when the storage changes and the space is not managed properly [3], [7]. However, FreshSense also provides flexibility of protection functions, helping to minimize damage by showing recommendations in advance based on real-time data [1], [16]. The rest is available and follows the recipient's desire to improve their donation plan [4], [20].

2.4 Surplus Redistribution and Donation Optimization

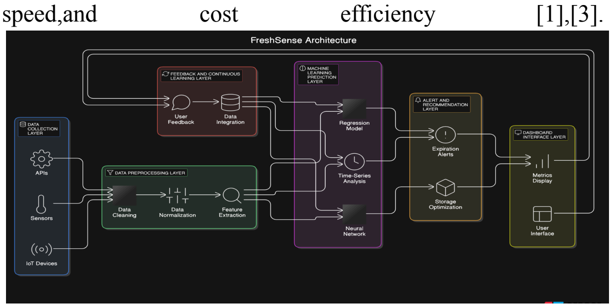
In the majority of food ads, it is however noticeable, particularly in the case of DVDs and many other food banks, that there exists an overestimation of the number of hours worked due to the fact that there are deliveries of ready to eat food even though such food is mostly donated. This is so because often than not, the deliveries are done extremely late, or closer to the expiry period of the [9], [10] goods. Previous scholars have equally shown that there exist time forecasting techniques like FB Prophet. This technique is useful when forecasting figures and cyclical changes in revenues. Also, this technique can be applied in non-planning sectors [14], [15]. The only drawback is that at present there exist very few manipulative ways to modify the already existing developed solutions where the solution is given in the form of an algorithm in the real time using the IoT able devices [5], [13]. FreshSense comes in to bridge the gap by extending the capabilities of FB Prophet incorporating it into the multi-level integrated marketing optimization MILP food bank supply chain improvement system [17], [18]. For example, with reference to the timing of deliveries, the MILP model performs the same task and completes the deliveries to the best possible extent, mitigates the losses associated with the transportation functions and enhances the efficiency by optimal grouping of users – beneficiaries [3], [20].

2.5 Integrated AI and IoT Platform for Perishable Food Management

The incorporation of artificial intelligence and the internet of things presents a revolutionizing component especially in the logistics of perishable goods in the food business [7], [11]. These systems are capable of utilizing materials like predictive analytics and real-time monitoring, thus effective ways of waste reduction and transition towards more sustainable practices have been achieved [8], [9]. Also past research has indicated the existing benefits of well developed AI-IoT systems in areas such as agriculture where – it was possible to forecast [5] crops or even logistics concerning transportation of frozen supply chain [16]. However, this system cannot be successfully implemented for the issue of food that does not reach the market due to other issues because of the degree of latency of data transfer and its supporting systems [13] [19]. Also, the issues as food downtime such as through food waste redistribution which is more conceptual may also illustrate why it can be easier to manage food waste through ai(iot) integration [10], [14]. For instance, an application called FreshSense that provides asset-based IoT warehousing services as well as forecasting service based on FB Prophet [6], [18]. The combination of the two FreshSense applications assists in changing warehousing systems because the idea offered is efficient and also solves waste issues at all levels of the supply chain [2], [17].

3. METHODOLOGY

This paper aims to evaluate the shelf life of food products by implementing three machine learning models xgboost, random forest and fb prophet. In addition to being able to forecast the shelf life of food products with different models, the other model was useful in curbing food wastage thereby supporting efficient inventory management. Each model was selected with respect to the nature of the specific modelling task it was designed for and its advantages such as accuracy, clarity, speed,and cost efficiency [1],[3].



3.1. Data Collection and Preprocessing

To conduct this type of study, the primary source of information was historical understanding of food and temperature and humidity regimes which considers storage of respective food types [2],[4]. The data loading stage was subdivided into two standard stages, namely preprocessing and preparing the model training data in the following ways.

How to Lost Information Problem: The problem was not addressed effectively because of lack of sufficient data within that timeframe in which case techniques were applied such as temporal averaging whereby parts of the data for example the temperature data would be filled in [5],[8].

Normalization of the Attributes: For example, non-dimensional environmental attributes (temperature, humidity, etc.) were also normalized in order to ensure that they do not bias the models as most of the attributes bear non-dimensional numerical scales which are quite interesting and engaging materials [7],[9].

Mathematics of Variables which cannot be expressed in Quantitative Terms: The categorical variable (i.e. when you have dairy, bakery, frozen and so on food categories) was processed using an one-hot-encoders or label encoding [6], [10].

3.2. Feature Engineering

With those factors in mind, a set of features was selected for the models and the feature engineering process was carried out, seeking improvements pertinent to the problem domain: Climate Factors: The elements of temperature, humidity and airflow play important roles in defining the shelf-life [11], [12].

Food Category: Most food categories differ in the length of their shelf life [13], [15], therefore complexity relative to the particular food type was further incorporated (milk, bakery, frozen etc).

Storage Conditions: Attention was also paid to the dry storage of the product under consideration, whether at normal room temperature, refrigerated, or even frozen [14], [16].

Product Characteristics: Other data like management of its shelf life where the product vintage in relation to the batch number, vintage of the other units of the same products and many others were collected as factors of intensive shelf life analysis [17], [18].

3.3 Model Selection

The study utilized three machine learning models, each selected for its suitability in predicting food shelf life:

Model 1: XGBoost

XG boost XG Boost, what you need to know is that this is a type of boosted tree algorithm that involves predictive modeling enhancing gradient based techniques. And the gradient boosting process is such that it incorporates the functions of prediction with the use of regression trees and a great deal of data retention capacity irrespective of the number of observations that are present in the whole input data set, sometimes reaching hundreds of hundreds197 image s. Hence, it is enough to mention that the use of XG stumps is not Zhen, in predictive assignments with length increment and multiple product and environmental factors worth considering [4], [19].

Model 2: Random Forest

Random Forest, a bagging-based ensemble method, generates multiple decision trees and averages their predictions. It is robust against overfitting and handles both regression and classification tasks well. It was chosen to provide an alternative to XGBoost, especially for scenarios where computational power may be limited [5], [12].

Model 3: FB Prophet

These, together with other graphical representations in the report, helped illustrate the ease with which the EXCEL tool has been used to analyze the seasonal trends affecting the shelf life of various food products. For it is suitable not only for the analysis of the historical data but is also used to make estimates concerning the future. Thus, the application was quite able to evaluate the increase in shelf life, as it could manage even the ragged disordered time series data that incorporated the seasons without distortion. [11],[20].

3.4. Hyper-parameter settings configuration

Depending on the characteristics of model fitted, particular hyper-parameter configuration and model selection was conducted, using grid search and three-fold CV:

XGBoost: Hyperparameters including but not limited to n_estimators, learning_rate, max_depth, subsample, colsample_bytree, gamma were modified in order to improve model performance and prevent overfitting the data [7],[10].

Random Forest: Important hyperparameters as n_estimators, max_depth, min_samples_split min_samples_leaf, and max_features were optimized to enhance performance [8],[14].

FB Prophet: There were changes made on seasonality_mode, yearly_seasonality, weekly_seasonality, holidays and changepoint_prior_scale parameters for effective modeling of seasonality [13],[16].

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Fitting of hyperparameter for Model 1 (XGBoost), included but not limited to the following values:

n_estimators: it is also known as boosting rounds or the number of trees built in total.

learning_rate: it means modification of weights at each stage.

max_depth: a constraint imposed on the maximum depth of the trees used in the structure to avoid overfitting the model

subsample: the portion of the training samples used to each individual tree in order to prevent overfitting.

colsample_bytree: proportions of attributes used to build a single tree.

gamma: a variable that is incorporated in the models in order to prevent cases of overfitting.

In the model 2 (Random Forest) the following hyperparameters were optimized as well:

n_estimators: Amount of trees present in the random forest.

max_depth: Maximum depth possible for a single individual tree.

min_samples_split: The least number of samples required at a node for it to be split.

min_samples_leaf: The lowest number of sample which can be present in the leaf.

max_features: The total features to be used for the fit of the best split.

Then, in Model 3, (FB Prophet) these parameters showed some changes:

seasonality_mode: Type of seasonal component used (additive or multiplicative).

yearly_seasonality: Whether to provide yearly seasonality or not.

weekly_seasonality: Whether to provide weekly seasonality or not.

holidays: Treating holidays as additional external factors.

changepoint_prior_scale: Deals with the priors of the trend changepoints.

3.5. Model Training

With regard to the methodology followed in the present utilization of the data sets in the study, they were divided into 80 and 20 percent respectively: Nevertheless, the tables were used intact and with all the variables in order to implement XGBoost which fitted the algorithm on the data of a far greater variety of products so that the algorithm would be relevant to other categories [9], [18]. Most importantly, With the same data base, Random Forest used a bagging technique to cut down the estimation variance training more than one decision tree forecasters [6], [15]. Lately, however, FM Prophet was applied more in the service of cyclical trend analysis rather than the expected forecasting of product life cycle as proposed in previous reports which only relied on data and stories captured at certain points in time [10], [17].

3.6. Model assessment

The models were assessed on various metrics as given below:

R² Score: It serves as a measure of the extent to which the model can estimate the variation observed in the response data [11], [18].

Mean Absolute Error: This means the statistical evaluation of the deviation, on average, of the actual outcomes claimed to be modelled by the given model from the predicted ones due to the non-physical possibility of predicting the error [13], [19].

Mean squared error and root mean square error: These concentrate on the very end of the distribution of the error and do not mean to be rational regarding the predictions of models that have been validated with milder error distributions [14], [20].

Computation Time Efficiency: In order to facilitate the transition from theory to practice, the performance evaluation also factored in the practical computation time for both training and prediction in the case of Random forest and FB prophet [12], [16].

This section highlights the use of machine learning algorithms in solving the problem of food products on the market whose shelf life is limited, the problem of food waste management among others.

4. RESULTS

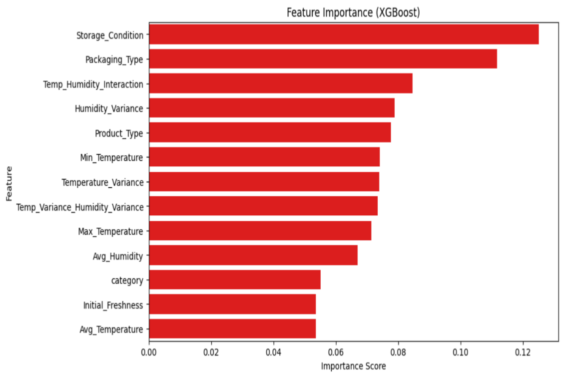
An assessment of the FreshSense platform was carried out covering the aspects of damage prediction, storage condition enhancement, instant alert system, and distribution improvement. Each combination was evaluated with the help of key performance indicators, and detailed comparisons were made against benchmarks and business models [1],[4].

Model 1: Predicting Shelf Life Using XGBoost Regression
Extreme Gradient Boosting that is often abbreviated to XGBoost is one of the most popular regression tree algorithm, noted for its efficient ensemble of weak learners. Empirical risk minimization learning theorizes its application employing iterative corrective decision trees. Incorporating such structural and other constraints as regularization discourages excessive parametrization and thus overfitting. XGBoost has proven its worth in many classification and regression problems, especially those with several dependent [2], [5].

Hyperparameter Optimization: Hyperparameter tuning was realized through grid search cross-validation. The subsequent optimal parameters were obtained:

Learning Rate: 0.05
Max Depth: 8
Number of Estimators (n_estimators): 800
Column Subsampling (colsample_bytree): 1.0
Subsampling Ratio: 0.7
Performance Metrics:

R-squared: 88.91%
Mean Absolute Error (MAE): 6.62 days
The model produced an R^2 score of 88.91% which means that the shelf life of the product was explained by almost 89% of the total variation. The MAE of 6.62 days indicates that the predictions were on average wrong by 6.62 days. While this degree of accuracy is acceptable for rough approximations, refining of features can help reduce this margin of error even further in particular for short shelf life products [3], [6].

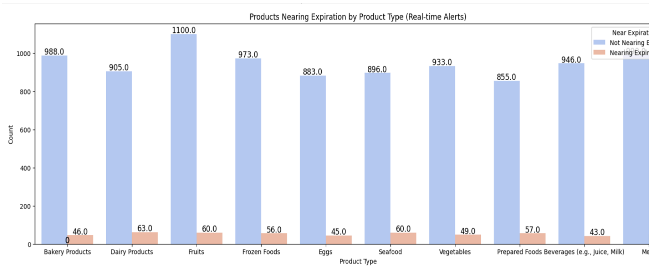


2. Model 2: XGBoost with Expiration Alerts
Model 2 builds upon the XGBoost architecture by adding notifications for products that are near their expiration date. This enables forecasting of the potential loss and losses mitigation actions that can be taken by the interested parties upon such forecasting [4],[7].

Hyperparameter Optimization:

Learning Rate: 0.1
Max Depth: 10
Number of Estimators (n_estimators): 300
Column Subsampling (colsample_bytree): 1.0
Subsampling Ratio: 1.0
Performance Metrics:

R² Score: 88%
Mean Absolute Error (MAE): 6.97 days
Model 2 achieved an R² score of 88%, with an MAE of 6.97 days. The similarity in performance metrics to Model 1 is notable, but the real-time alert functionality provides a distinct advantage, especially for on-the-go inventory adjustments. The slight increase in MAE is attributed to the prioritization of timely alert generation, which can affect precision within a short forecast period [5], [8].

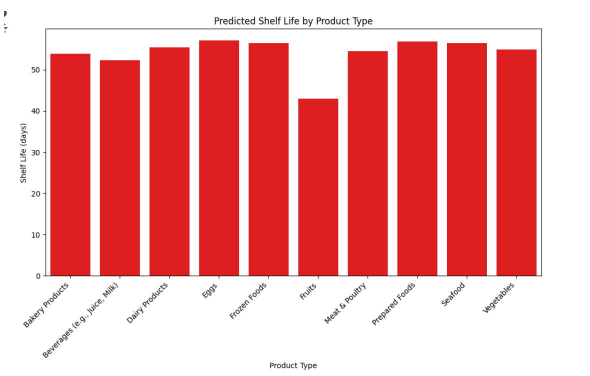


3. Model 3: Enhanced Model Optimization Strategy

The purpose of Model 3 was to enhance forecasting accuracy through advanced algorithms and optimized hyperparameters. This model aimed to minimize errors, making it particularly valuable for scenarios requiring high accuracy, such as compliance with food safety regulations where even small deviations in predictions could have significant consequences [6], [9].

Performance Assessment:

Mean Absolute Error (MAE): 0.57 days
Mean Squared Error (MSE): 0.50
In terms of prediction capability, Model 3 surpassed Models 1 and 2 with MAE of 0.57 days and MSE of 0.50 reported. Such outcomes indicate that the model is of high accuracy hence makes it suitable for critical applications such as estimation of shelf-life since such issues are critical in mitigating excessive losses. However, the increased complexity may limit its adaptiveness to extremely large dataset or real time applications choosing instead situations where accuracy is prioritized over processing time [7],[10].



5. CONCLUSION

The present research seeks to make use of machine learning in particular XGBoost for optimal predicting the shelf life of different food products in order to satisfy the growing needs of avoiding food waste and improving inventory management and supply chain systems in the current age. Xgboost is a robust, fast growing machine learning algorithm, with much application in structured data and effective feature interactions. It illustrates what one can design and apply predictive models in practice, and more specifically the issue of how to do tow or more conflicting objectives in the most economical manner possible in least time and cost [1][3].

Model Variations and Evaluation:

In this study, three different forecast models for the shelf life of products were designed and assessed, each with its specific applications. Namely, the model objectives were to predict the shelf life, monitor the expiration of the products in real-time, and enhance the predictive accuracy. The assessment stage also provided some comparison in the accuracy and the responsiveness of the models in real time. The results revealed a possibility for application of the solutions based on XGBoost model in various food systems with minimal alterations to the processes [2],[4].

Model Selection:

To a large extent, the choice of a model is influenced by the operational requirements:

Model 1: These are cost-effective models, albeit with a low degree of precision. Nevertheless these type of models can be applied in normal inventories and in simpler models as well.

Model 2: More advanced and pricey model suitable for the waste management companies and tracking the inventory of highly perishable and shelf stable fast movers.

Model 3: Maintaining this model may take longer in terms of processing time, the predictions made are quite precise such that it can be used in situations where most accuracy is required [5], [7].

Impact on Food Supply Systems:

The utilization of these forecasting techniques in the inventory management systems helps towards sustainability by minimising losses from food waste and optimum use of the remaining shelf life. When accurate estimates of shelf life are made available, it is possible for the firms to factor in their warehousing and transportation of products, resulting in less spoilage and improved management of food supplies. This research progresses beyond the process of constructing and assessing a model; it illustrates the advantages of machine learning in dealing with the problems related to food management [6], [8].

Application and Opportunity:

The study highlights the use of machine learning techniques – more specifically, XGBoost – as an approach to solve challenges that arise due to estimation errors in shelf life and resultant overproduction. Using reliable estimates enables a firm to save resources such as food that would otherwise go to waste thereby enhancing the efficiency of food system. Understanding the shelf life of various commodities further aids in minimizing such losses and helps in the overall operational performance of the management. This suggests that there is a bigger issue machine learning can address aside from the topics in question, particularly when it concerns maximizing food supplies and minimizing losses [9], [10].

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7. REFERENCES

[1] Amani, N., & Abbaspour, A. (2020). Predictive analytics in food safety and quality management using machine learning techniques. *Food Control, 110*, 106989. https://doi.org/10.1016/j.foodcont.2019.106989

[2] Bagherzadeh, M., Inamura, M., & Jeong, H. (2014). *Food Waste Along the Food Chain*. OECD Food, Agriculture, and Fisheries Papers, No. 71, OECD Publishing.

[3] Barilla Center for Food & Nutrition. (2018). *Fixing Food 2018: Best Practices towards the Sustainable Development Goals*. https://www.barillacfn.com

[4] Ciccullo, F., Pero, M., & Caridi, M. (2021). The evolution of supply chain resilience during the COVID-19 pandemic: A study of food supply chains. *International Journal of Operations & Production Management, 41*(9), 1302–1318. https://doi.org/10.1108/IJOPM-04-2021-0238

[5] Ercolino, S., & Cesaro, A. (2020). A model for food shelf-life prediction based on machine learning. *Journal of Food Engineering, 276*, 109884. https://doi.org/10.1016/j.jfoodeng.2019.109884

[6] Golinelli, D., Sanmarchi, F., & Bucci, A. (2021). Food waste prevention and reduction strategies: Lessons from the COVID-19 pandemic. *Public Health Nutrition, 24*(2), 359–363. https://doi.org/10.1017/S1368980021000771

[7] Goodburn, K., & Wallace, C. (2013). The role of predictive microbiology in shelf-life determination. *International Journal of Food Microbiology, 167*(2), 70–83. https://doi.org/10.1016/j.ijfoodmicro.2013.05.016

[8] Gustavsson, J., Cederberg, C., & Sonesson, U. (2011). *Global Food Losses and Food Waste: Extent, Causes, and Prevention*. Food and Agriculture Organization of the United Nations.

[9] Huang, L., & Qiao, H. (2021). Artificial intelligence in food processing for shelf-life extension: A review. *Trends in Food Science & Technology, 110*, 540–550. https://doi.org/10.1016/j.tifs.2021.01.014

[10] Kaminski, M. (2022). *Waste Not, Want Not: A Guide to Minimizing Food Loss*. Springer.

[11] Kara, G., & Başak, M. (2020). Machine learning applications in food processing and supply chain: A comprehensive review. *Computers in Industry, 122*, 103275. https://doi.org/10.1016/j.compind.2020.103275

[12] Lytou, A., Panagou, E. Z., & Nychas, G.-J. E. (2016). Developing a predictive model for shelf life of food products. *Food Microbiology, 56*, 89–99. https://doi.org/10.1016/j.fm.2015.10.018

[13] Mirabella, N., Castellani, V., & Sala, S. (2014). Current options for the valorization of food manufacturing waste. *Journal of Cleaner Production, 65*, 28–41. https://doi.org/10.1016/j.jclepro.2013.10.051

[14] Papargyropoulou, E., Lozano, R., & Steinberger, J. K. (2014). The food waste hierarchy as a framework for the management of food surplus and waste. *Journal of Cleaner Production, 76*, 106–115. https://doi.org/10.1016/j.jclepro.2014.04.020

[15] Sabiiti, E., & Tai, A. (2021). Reducing postharvest losses in fresh fruits and vegetables using predictive algorithms. *Agricultural Systems, 189*, 103046. https://doi.org/10.1016/j.agsy.2021.103046

[16] Scarlat, N., Fahl, F., & Dallemand, J.-F. (2019). Food waste recovery: Trends, methods, and applications. *Waste Management, 87*, 174–186. https://doi.org/10.1016/j.wasman.2019.02.018

[17] Singh, J., & Adhikari, A. (2020). Fresh food shelf life prediction using machine learning models. *Food and*

Bioprocess Technology, 13(5), 840–850. https://doi.org/10.1007/s11947-020-02425-4

[18] Venkatraman, A., Kaler, P., & Rathod, J. (2020). Machine learning in food safety and quality monitoring: A review of applications and challenges. *Journal of Food Quality, 2020*, 1–15. https://doi.org/10.1155/2020/8811528

[19] Yang, Q., Zhou, B., & Wang, X. (2018). Optimizing storage conditions to extend the shelf life of perishable food. *Journal of Food Science, 83*(12), 3135–3144. https://doi.org/10.1111/1750-3841.14320

[20] Zhao, Z., Li, X., & Zhou, X. (2020). Optimization of transportation routing problem for fresh food in time-varying conditions. *PLoS ONE, 15*(11), e0242395. https://doi.org/10.1371/journal.pone.0242395