An Offline Digital Twin for Resilience and Supplier Reliability in Perishable Food Supply Chains

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Abstract

Supply chain resilience and supplier reliability are crucial for highly perishable agricultural goods. The disruptions in these supply chains can severely affect perishable goods, leading to revenue loss. This research proposes an approach that integrates iterative simulation and machine learning techniques to assess the supply chain's resiliency and predict the supplier's reliability in the perishable strawberry supply chain. The methodology begins by generating data for involved entities to replicate real-world dynamics. A discrete-event simulation environment helps in modeling intricate supply chain interactions, capturing time-dependent events, and evaluating the impact of disruptions in a controlled virtual environment. The model forecasts supplier reliability scores, introducing dynamism and uncertainty into the simulation. The model is trained for machine learning, training, and evaluating multiple classifiers, such as XGBoost, Random Forest, SVM, Logistic Regression, KNN, Naive Bayes, and Decision Tree, for predictive and comparative performance. Sensitivity analysis is conducted to test the robustness of the predictive model by varying input parameters. Integrating this predictive model with the perishable product supply chain enhances decision-making, enabling proactive measures to be taken in response to potential supplier shutdowns. The proposed approach provides a comprehensive and practical solution for improving supply chain resilience and managing supplier reliability in the strawberry supply chain. Integrating simulation and machine learning techniques helps the supply chain decision-makers optimize involved operations and mitigate disruptions, benefiting the entire food supply chain ecosystem. Hence, this research offers valuable insights into improving the supply chain for perishable goods and supplier reliability. The findings help decision-makers devise strategies and timely choices to sustain a robust and reliable supply chain.

Keywords
Discrete-event Simulation, Machine Learning, Perishable Food Supply Chain, Supplier Reliability, Supply Chain Resilience.

1. Introduction
Food supply chains (FSCs) are dynamic and complex, with many interrelated processes, players, and difficulties. Those intricate networks consist of a series of interlinked processes involving multiple stakeholders, transportation systems, storage facilities, and distribution channels (Ali et al. 2021; Messina et al. 2020), as shown in Figure 1. FSCs have a complicated network of activities, including cultivation, processing, distribution, and consumption, from production to consumption. Hence, it is crucial to ensure the quality of food and its safety through the supply chain (SC). Each stage involves a balance of resources, planning, and coordination to ensure a seamless flow of goods (Singh et al. 2021). FSC disruption is a breakdown in a SC's production, distribution, or consumption processes due to unanticipated incidents, risks, or accidents. They are vulnerable to disruptions, and global coverage makes them more susceptible to risks involved in transmissions (Ali et al. 2021). Natural disasters like hurricanes, floods, and droughts can adversely impact agricultural production and transportation, leading to crop failures, delayed shipments, and increased prices. Extreme events, such as droughts, heavy rains, and plant diseases, also reduce crop yields and cause food shortages, resulting in food insecurity (Reardon and Swinnen, 2020). Geopolitical tensions, trade conflicts, and

economic downturns can disrupt trade routes and lead to SC bottlenecks. Therefore, SCs should be analyzed holistically to minimize the impact of disruptions on performance (Olivares-Aguila and ElMaraghy, 2021). FSCs face opportunities and challenges due to globalization (Messina et al. 2020; Moosavi et al. 2022). Food products travel large distances and frequently cross-national borders and long-distance transportation. In recent times, unexpected events like the COVID-19 pandemic have further highlighted the fragility of FSCs, as restrictions, lockdowns, and labor shortages disrupted distribution channels and hindered the availability of perishable food items. These food items have a short shelf life and must be handled carefully to preserve quality and avoid deterioration.

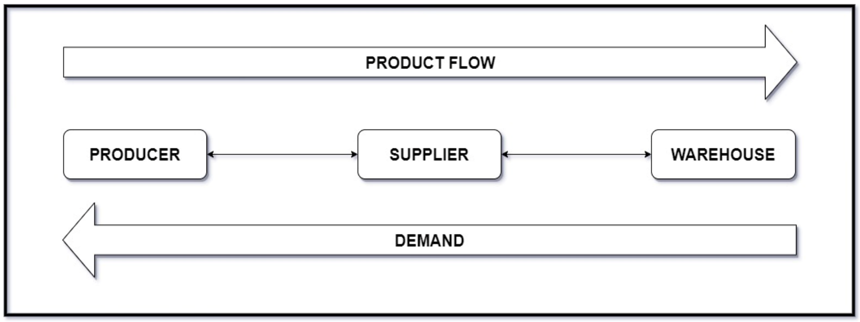

Figure 1. Food Supply Chain

Resilience is the capability of SCs to recuperate from disruptions and sustain effective operations. Although a perfect SC can never be designed, understanding the system's behavior and potential implications can help mitigate disruption impacts and achieve SC resiliency (Olivares-Aguila and Vital-Soto, 2021). Elements influencing the resilience of FSCs encompass their structural design, infrastructure, information exchange, and governmental regulations. Resilient FSCs often exhibit features like diversity, redundancy, and adaptability (Reardon and Swinnen, 2020). Strategies for enhancing resilience play a pivotal role in combatting disruptions and bolstering the ability to withstand and rebound from these interruptions (Kumar and Kumar Singh, 2022). Therefore, achieving optimal visibility at each stage of the FSC requires cohesive interaction among its constituents (Al-Talib et al. 2020). Golan et al. (2020) emphasized using advanced analytical methodologies in resilience analytics, including modeling, simulation, data analytics, network analysis, and multiobjective optimization, to assess and enhance SC resilience, including scenario analysis, network analysis, data analytics, and multiobjective optimization. Similarly, Hosseini and Ivanov (2022) proposed a multi-layered Bayesian Network method consisting of demand, supply, and external environment layers, which studies these scenarios.

Perishable food supply chains (PFSCs) face unique challenges due to the time-sensitive nature of their goods, making them susceptible to disruptions that can have far-reaching consequences on food safety, quality, and availability. These disruptions lead to logistics bottlenecks and unpredictable suppliers' reliability and performance. These disruptions result in delays, product wastage, and cost increases, directly affecting the consumers. The vulnerable points and potential improvement areas can be evaluated for resilience. As such, assessing SC resilience and accurately predicting supplier reliability become pivotal to safeguarding this essential sector and ensuring uninterrupted access to fresh, safe, and nutritious food for consumers worldwide.

Strawberries, known for their delicate nature and high perishability, are among the most wasted fruits throughout FSCs (Buzby et al. 2009; do Nascimento Nunes, 2009; Legard et al. 2000; Nunes and Emond, 1999; Terry et al. 2011). The deterioration of strawberry quality begins at the farm and progressively accumulates throughout the SC, leading to significant losses. However, the level of impact at each SC step on strawberry quality and the critical stages where quality decline is most pronounced remains to be determined. Temperature, a crucial environmental factor, profoundly affects strawberry quality and shelf life (Ayala-Zavala et al. 2004; do Nascimento Nunes, 2009; Kalt et al. 1993; Lai et al. 2011; Nunes and Emond, 1999). Combined waste at the suppliers and warehouse levels could reach as high as 28% (Buzby et al. 2009; Gustavsson and Stage, 2011; Nunes et al. 2009; Terry et al. 2011). At the supplier level, approximately 5-10% of strawberries are deemed unacceptable for sale and discarded (Porat et al. 2018). These factors make it essential to devise policies for strawberry's SC to reduce wastage and optimize the SC at the supplier stage.
One of the critical challenges this industry faces is ensuring a smooth and efficient SC to deliver fresh produce from producers to consumers. The traditional methods used to assess and manage SC risks may not be sufficient to address

the difficulties faced. It is necessary to employ advanced techniques such as simulation and machine learning (ML) to proactively evaluate the SC's vulnerabilities and predict the reliability of suppliers.

ML algorithms can analyze vast amounts of historical data to identify patterns and trends, enabling better supplier performance and SC behavior prediction. The prediction of supplier reliability beforehand allows SC managers to optimize their decision-making, such as selecting reliable suppliers, adjusting inventory levels, and formulating contingency plans for potential disruptions. Using simulation models, decision-makers can gain valuable insights into potential disruptions and explore strategies to mitigate their impact. The research outcomes are expected to contribute to developing robust SC strategies that can minimize the impact of disruptions and ensure the timely delivery of high-quality strawberries to consumers. It becomes crucial for stakeholders to develop resilient strategies to withstand disruptions and provide a steady flow of perishable materials to the market. This research aims to evaluate the resilience of the strawberry SC and predict the reliability of suppliers, which will help in enabling preventive and proactive measures to be taken in times of potential disruptions. This article is organized as follows. Section 2 analyzes the most representative studies regarding digital twins in the food industry and supplier selection methods. Section 3 introduces the proposed offline digital twin for the perishable FSC. In section 4, results and analysis are discussed. Finally, in section 5, conclusions and future research avenues are presented.

2. Literature Review

There has been tremendous growth in population in the world, leading to increased food demands. Food production must meet this increasing demand. One of the critical challenges this industry faces is ensuring a smooth and efficient SC to deliver fresh produce from producers to consumers. SC disruptions can lead to significant losses, especially when dealing with perishable goods. SCs' intricate and global nature has led to more reliance on the supplier's network. These complexities sometimes expose SCs to significant levels of risk (Gao et al. 2019). Rajesh and Ravi (2015) stressed the necessity of resilience for suppliers to adapt to disruptions and be flexible enough to accommodate fluctuating demands. Ivanov et al. (2019) categorized SC resilience as the web of non-failure operations, durability, recoverability, and the maintenance of overall SC processes.

Supplier selection constitutes how organizations assess, categorize, and determine potential suppliers to align with their specific business requirements (Govindan and Sivakumar, 2016). Once a reliable supplier is identified, the efficacy of the SC significantly impacts customer satisfaction (Amin and Baki, 2017). Hamdi et al. (2018) emphasized how an optimal supplier helps deliver the right product at the right time, location, and quantity. This dynamic has prompted the integration of resilience into supplier selection processes due to the significant risk exposure (Gao et al. 2019; He et al. 2019; Hosseini and Ivanov, 2022; Ivanov et al. 2017; Larson and Chang, 2016; Weber and Current, 1993).

In PFSCs, supplier selection plays an important role. Supplier evaluation primarily revolves around aspects such as delivery times and past supplier performances (Babbar and Amin, 2018; Chai and Ngai, 2020). Various studies have explored the gaps between supplier selections and risk management within SCs (Hamdi et al. 2018; Rajagopal et al. 2017). During disruptions, supplier-customer relationships are pivotal, paving a path for reliable suppliers throughout longer durations (Chen et al. 2016; Sheffi and Rice Jr, 2005; Wu and Olson, 2008). The efficiency of the supplier selection process depends on the accuracy with which decision-makers evaluate potential suppliers. Although many studies have been on supplier selection strategies, only some explore data analytics' role in selecting resilient suppliers (Cavalcante et al. 2019).

Digital technologies to improve SC resilience, such as big data analytics, blockchain, and digital twins, have been proposed in the literature as they can leverage the value of information to allow preparedness and recovery for unexpected events (Saravanan et al. 2022). A digital twin is a technology that builds virtual models of physical entities. It helps in tracking the progress of the present product in real-time through bidirectional cyber-physical interactions. It helps to control decisions and helps in the assessment of product changes. The offline digital twin is a virtual representation of a physical object, process, or system created and maintained separately from the real-time data and operations, allowing for analysis, simulation, and testing without affecting the actual entity. It enables predictive insights and optimizations while disconnected from live operations (Seid Ahmed and ElMaraghy, 2023).

Digital SC twins, as defined by Ivanov et al. (2019), are computerized representations of network states at specific moments. These models mirror the actual SC with accurate data on transportation, inventory, demand, and capacity (Cavalcante et al. 2019). They serve decision-makers by enhancing end-to-end SC visibility, resilience, and contingency planning and for the urgency of visualizing SC networks arising from growing disruptions (Dolgui et al. 2020). These digital twins offer real-time transparency on crucial logistics data, inventory, service levels, etc. They act as data-driven control towers and simulation tools for efficient contingency strategies (Burgos and Ivanov, 2021; Ivanov and Dolgui, 2021). They use the network to integrate the customers, factories, and suppliers. Flows depict SC specifics with adaptable production, inventory, sourcing, and shipment policies. Operational parameters encompass demand, lead time, and control thresholds for simulations, optimization, and disruption analyses.

Artificial intelligence solutions applied to cyber-physical systems (CPS) enable ML inference on abundant data collected from Internet-of-things (IoT) devices, benefiting from their increasing accuracy (Loseto et al. 2022). ML techniques within the Industry 4.0 framework empower diverse industrial sectors with real-time process monitoring and control. This stems from practical data analysis and prediction facilitated by ML models trained on extensive IoT-generated information. The synergy between ML, IoT, and data analysis advances CPS, significantly enhancing industrial performance. Tancredi et al. (2022) proposed an integrated approach, uniting digital twin models, ML algorithms, and Industry 4.0 technologies.

Similarly, Krupitzer et al. (2022) integrated food science models and simulations with data-driven ML-based data analysis to create a hybrid strategy for developing digital food twins. Usuga Cadavid et al. (2020) presented an approach considering diverse data sources such as raw materials, machine metrics, and customer information. Cioffi et al. (2020) highlighted the ML role in enhancing production planning. Moreover, Abideen et al. (2021) proposed a new approach to analyzing the risk profiles of supplier performance under uncertainty by combining simulation and ML in integrated digital SC twins. These twins improved resilience by learning and designing risk mitigation strategies in SC disruption models, re-designing the supplier base, or judging the most critical and risky suppliers.

Several digital twin implementations in the food industry have been proposed in the literature. Most of the digital twin applications in this sector are related to the SC transportation function to monitor changes in the quality of fresh produce through the cold chain (Dy et al. 2022). Also, digital twins have been proposed to evaluate the resilience of a food retail SC (Burgos and Ivanov, 2021) and a last-mile distribution system for food during the pandemic (Sharma et al. 2020). While significant strides have been made in the field of SC management, particularly in the context of perishable agricultural goods, there remain notable research gaps that necessitate the proposed approach's investigation. Firstly, the existing literature predominantly focuses on generalized SC resilience and reliability measures, often overlooking the unique challenges posed by highly perishable goods such as strawberries. These challenges include stringent time constraints, temperature sensitivity, and rapid decay rates, which demand specialized strategies for ensuring SC robustness. Another aspect is while simulation models and ML techniques have been applied individually to enhance SC decision-making, there is a shortage of studies that integrate both approaches to comprehensively assess SC resilience and predict supplier reliability. By bridging this gap, our research aims to provide a holistic solution that accounts for the dynamic, time-dependent nature of perishable SCs while leveraging the predictive power of ML.

The research community lacks a standardized framework for evaluating supplier reliability in perishable SCs, which results in a fragmented understanding of this critical aspect. Our study seeks to address this gap by proposing a supplier reliability scoring model that can be applied generally, enabling cross-comparisons and benchmarking across different perishable SCs. The existing research often fails to provide actionable insights for SC decision-makers to manage disruptions caused by supplier failures proactively. Our approach aims to fill this gap by offering a practical decision-support tool that can assist stakeholders in optimizing operations and responding swiftly to potential supplier shutdowns. In summary, this research bridges several notable research gaps within the field of perishable SC management by (1) focusing on the unique challenges posed by highly perishable goods, (2) integrating iterative simulation and ML techniques, (3) proposing a supplier reliability scoring model, and (4) providing actionable insights for enhancing SC resilience. By addressing these gaps, our study contributes to a deeper understanding of perishable SC dynamics and offers practical solutions for stakeholders in the agricultural and food industries.

3. Offline Digital Twin for Perishable Food Supply Chain

This section presents the detailed research methodology devised in this study to evaluate PFSC resilience and predict supplier reliability in the strawberry SC. The research focuses on developing a simulation and ML-based digital twin for the perishable SC of strawberries, as shown in Figure 2. The challenges involved in PFSCs are addressed by utilizing simulation modeling using discrete-event simulation framework and ML techniques. The research methodology chronologically consists of data collection, simulation environment setup, simulation entity classes, reliability forecasting, simulation iterations without and with suppliers' shutdown, feature engineering, and data preparation for ML.

The digital twin requires as input the SC structure (i.e., the number of producers, suppliers, and distribution centers), the warehouse demand (i.e., the number of transactions required each day), a predefined reliability score for each supplier, and a specified time frame for analysis. For demonstration purposes, a dataset containing information about producers, suppliers, warehouses, and demand quantities is generated randomly as input for the simulation model. However, that information can be gathered to be utilized in this methodology. Moreover, each product (e.g., strawberry batch) has an associated perishability level and quality deterioration rate. That data is unknown; hence, to check the supplier reliability based on on-time delivery, perishability level, and deterioration rate randomly assigned to each product.

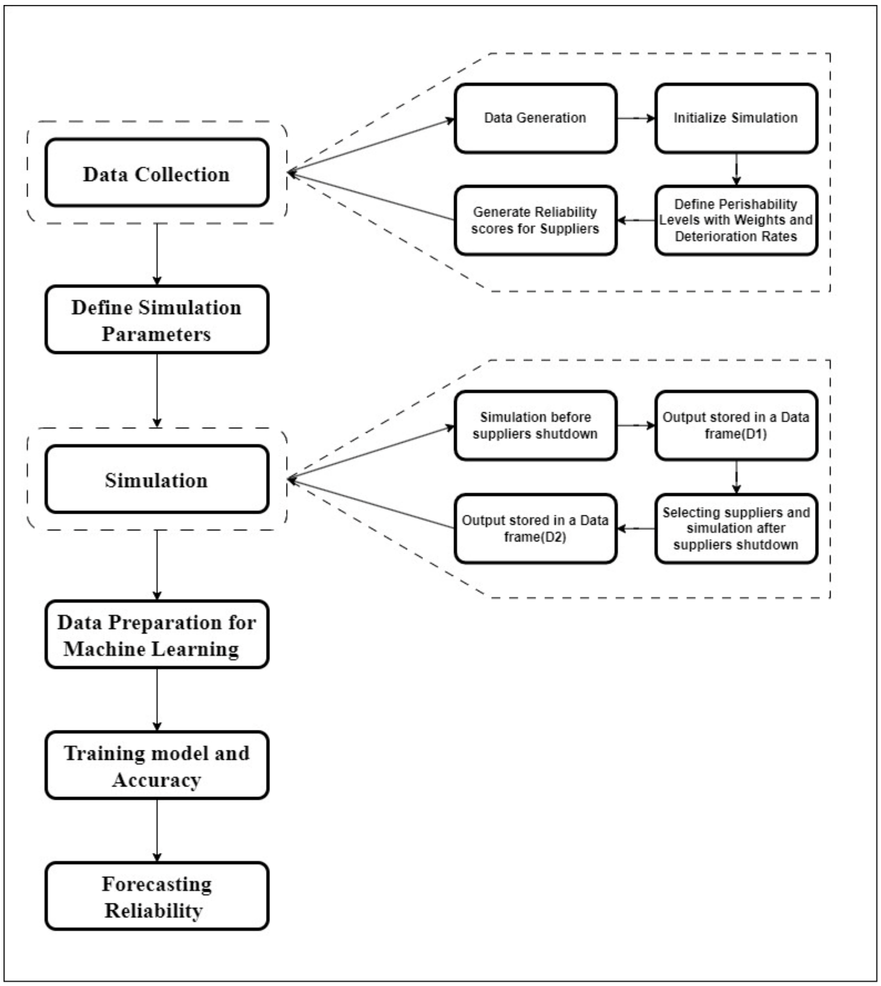

Figure 2. Offline digital twin for perishable food supply chains

The perishability level for strawberries is a crucial characteristic of the simulation. These perishability levels are randomly assigned to each batch, representing how quickly the strawberries deteriorate or spoil over time. The simulation categorizes the strawberries into three levels of perishability: Low, Medium, and High. Each perishability level is associated with specific weights and their quality deterioration rates. The quality deterioration rate indicates how much the quality of strawberries deteriorates during the whole SC process, and it varies based on the respective perishability level.

The simulation model replicates the operations of the strawberry SC under normal conditions in a virtual environment. Hence, the supplier selection process will consider the suppliers' reliability scores while simulating. Then, the simulation introduces disruption events by randomly closing several suppliers for the given period. This enables us to study how the disruptions may affect the SC's performance and the strawberry's quality. Multiple iterations of the simulation model are conducted to explore different supplier combinations and assess their impact under various disruption scenarios over different iterations of the SC. Historical data obtained from the simulation, assuming it remains the same and adequately represents the future SC dynamics, is used to train ML models for supplier selection. The ML models consider factors such as supplier reliability, past scores, historical strawberry quality data, and other relevant features to predict the most suitable suppliers for future transactions. More details about the simulation, ML models, and forecasted reliability are presented in sections 3.1, 3.2, and 3.3.

Several assumptions are made to simplify and streamline the research. It is assumed that the dataset generated for the simulation represents a realistic scenario, although it is generated randomly. The disruption events will be limited to the closure of a subset of suppliers, neglecting other potential disruptions such as transportation delays or natural disasters.

3.1. Simulation Model

The central part of this research is the simulation environment, which aims to emulate the real-world dynamics of the strawberry SC. The SimPy library is used for its flexibility in modeling complex systems with time-based events. The simulation environment is initialized using the SimPy Environment class. Three classes are defined to model the interactions between entities in the SC: Producer, Supplier, and Warehouse. Each class represents the behaviors and actions of the respective entities. The Producer class simulates the production process; the Supplier class simulates the supply process considering reliability scores and quality deterioration rates; and the Warehouse class simulates the storage process. These classes imitate the essential functionalities of the SC entities. The simulation process represents the sequence of actions performed in the strawberry SC for each transaction.

The process involves a producer yielding the required quantity, a supplier supplying the product with potential quality deterioration, and a warehouse storing the amount received. Each entity is represented by an instance of the respective class defined for the simulation. A simulation loop is implemented to simulate multiple iterations of the SC process. Each iteration runs the simulation twice: before the shutdown of suppliers and after the shutdown. Within each iteration, transactions are selected for each day of the simulation duration for the specific day and product type. Supplier data is merged with the transactions, and suppliers are chosen based on their reliability scores. Before the shutdown, the selected suppliers are stored in a data frame. A specified number of suppliers are chosen randomly, and others are shut down by setting their reliability scores to zero. After the shutdown, the process is repeated, and the selected suppliers are stored in another data frame.

3.2. Reliability Forecasting, Forecasted Reliability, and Feature Engineering

The research introduces a novel feature of forecasting supplier reliability scores to introduce dynamic behavior and uncertainty into the simulation. The objective of supplier reliability forecasting is to predict potential disruptions in the SC caused by multiple variations in supplier reliability. The original supplier reliability scores are taken as the input, and the forecasted reliability scores are returned. Then, feature engineering is performed on the transaction data. Binary lists are created to classify whether a supplier was selected before and after the shutdown. Lists of perishability level weights and quality deterioration rates for strawberries are also made. Lists of on-time and late deliveries for transactions are generated, and demand variability is introduced randomly. All these lists are added as new columns to the transaction data frame. The supplier's historical reliability scores and the duration for which reliability scores must be forecasted are taken as input.

The multiple ML models, which capture inherent patterns and trends within the historical data, are chosen for the same; in section 3.3, more details about the models are provided. By applying this approach, forecasts for supplier reliability scores are generated over a predefined duration. The generated forecasts allow us to explore potential scenarios involving changes in supplier reliability. These scenarios are crucial for understanding the potential challenges and risks that SC managers might face. The forecasted reliability scores are stored in different data frames.

3.3. Supplier Statistics, Data Preparation, and Machine Learning Model Training and Evaluation

Descriptive statistics such as the mean and standard deviation of the quantity for each supplier are computed using the transaction data. The supplier statistics are then merged with the transaction data using the Supplier ID's. This step ensures that the transaction data contains supplier-specific information for the training process. The transaction data is updated with the new columns and supplier statistics, preparing it for ML training. The prepared data is used for training the predictive ML models. The relevant functions are divided into features and the target variables. The target variable is a binary array consisting of 1s for the iterations before the shutdown and 0s for the iterations after the shutdown. In ML model selection and training, data is divided into training and testing sets, with a 20% allocation for testing.

The ML models forecast supplier reliability scores after training on both before-shutdown and after-shutdown scenarios. Various models are chosen for evaluating supplier shutdown prediction in the strawberry SC. These encompass the XGBoost and Random Forest Classifiers, known for their accuracy and handling of intricate data; the SVM and Logistic Regression Classifiers for linear and non-linear classification; and KNN and Gaussian NB Classifiers for proximity-based and probabilistic classifications. Employing the fit method in sci-kit-learn, these models are trained on the training dataset and optimized using grid/randomized search and cross-validation. Model evaluation on the testing dataset follows, employing metrics like accuracy, precision, recall, and F1-score to gauge predictive performance: these measures, supplier reliability scores, and quality deterioration rates guide model selection. The study observes how parameter modifications impact accuracy, aiding in model fine-tuning.

4. Results and Discussion

In this section, we present the results of our research, beginning with the outcomes of the supplier reliability forecasting process (Section 4.1). Subsequently, we delve into an extensive assessment of the performance of various ML models in predicting supplier reliability disruptions (Section 4.2). Finally, we offer an in-depth analysis of the findings, shedding light on their implications for SC management (Section 4.3).

4.1 Supplier Reliability Forecasting

In PFSCs, supplier reliability is critical to delivering the products and reducing loss due to their perishable nature. Hence, supplier reliability is assessed as a proxy of SC resilience. Elaborating on the reliability assessment, the multiple ML models generated the forecasted supplier reliability scores. This comparison provides valuable insights into the model's accuracy in predicting shifts in supplier reliability. By aligning forecasted and actual scores across different reliability levels, we quantified the model's predictive precision and capacity to inform SC managers about potential disruptions and associated risks. In this case, the ML model with the highest accuracy, Naïve Bayes, is used for graphical interpretation.

Figure 3 shows the reliability graphs for two different suppliers among a set of suppliers. They represent the extreme cases of supplier reliability forecasting. That is, in Figure 3, chart A), it can be observed that the actual reliability of that supplier ranges from 0.82 to 0.98 during the ten days of simulation. Moreover, it can be noted that when the ML model is implemented to forecast reliability, the predicted reliability scores reach almost 0.86. Similarly, in Figure 3, chart B), it can be observed that the forecasted reliability scores are nearly 0.94. By evaluating the forecasts across different reliability levels, we gained insights into the varying degrees of impact that different levels of supplier reliability could have on the overall SC performance. This approach comprehensively evaluates the model's reliability in supporting effective SC decision-making.

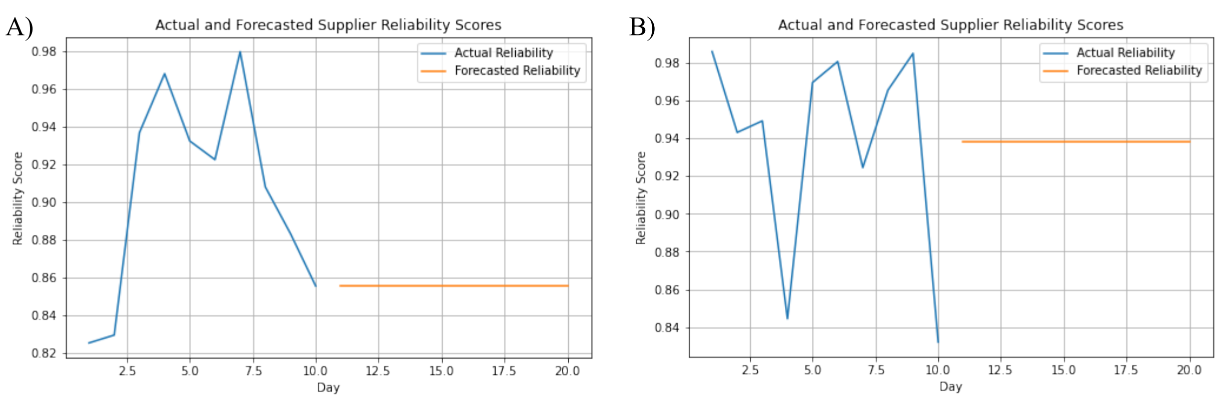

Figure 3. Extreme cases of actual and forecasted supplier reliability score

4.2 Machine Learning Model Performance

The performance of ML models is aimed at providing an understanding of their predictive capabilities for supplier reliability forecasting. Various ML algorithms and features are used to explore the models' potential to assess the patterns and relationships for the simulated SC historical data. The chosen algorithms encompass traditional methods such as Logistic Regression, Decision Tree, and Gaussian Naive Bayes, as well as advanced techniques like XGBoost, Random Forest, Support Vector Machine, and K-Nearest Neighbors. This selection of various models facilitates a holistic evaluation of their strengths and weaknesses in capturing the intricacies of SC disruptions.

Multiple evaluation metrics beyond accuracy, precision, recall, and F1 score were considered, as they provide a better understanding of the models' capabilities in correctly classifying supplier reliability disruptions. These metrics account for false positives and negatives, showing models' ability to minimize type I and II errors. Additionally, confusion matrices are constructed to visually depict the models' performance in differentiating between reliable and unreliable suppliers. A confusion matrix summarizes the performance of a ML model on a set of test data. Figure 4 shows the confusion matrix for the Naïve Bayes model.

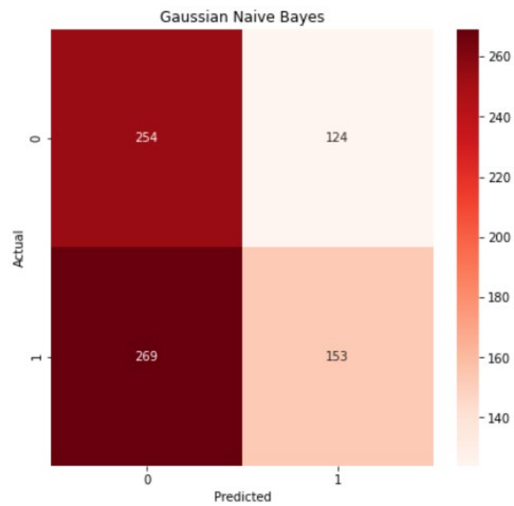

Figure 4. Confusion matrix for Naïve Bayes classifier

Moreover, cross-validation methodology is employed to ensure the robustness of all the models. Cross-validation involves partitioning the data into multiple subsets and training/evaluating the models on different combinations. This technique allows for assessing the models' performance across diverse scenarios, preventing overfitting and providing insights into their generalization abilities.

Figure 5 shows the accuracy of ML models after applying the cross-validation individually. The ML model assessment outcomes show the multifaceted nature of predicting supplier reliability disruptions. The performance of the models reflects the difficulties in predicting supplier reliability, which is influenced by complicated SC connections. The various ML models give an accuracy between 48 and 50%, as shown in Figure 5. These results are slightly better than the research carried out by Cavalcante et al. (2019), which gives a maximum accuracy of 45%. This study also employs an iterative simulation process, which is performed automatically by only indicating the required number of iterations and can be employed independently. The research carried out by Cavalcante et al.(2019) used AnyLogic software in which manual experimentations were required for the same.

4.3. Analysis

This analysis dives deep into the insights obtained from supplier reliability forecasting and the ML model performance assessments, highlighting key revelations that hold significant implications for effective perishable FSC management. Supplier reliability forecasts may help the SC decision-makers with insights for proactive decision-making for responses to potential setbacks, ultimately bolstering SC resilience. Although the accuracy ratings for ML may, at first glance, seem modest, they reveal the complex nature of forecasting supplier reliability disruptions and give a glimpse at the various factors that affect the stability of the SC. A multifaceted picture is revealed when combined with precision, recall, and F1-score measures. It becomes clear that the models need help recognizing trustworthy vendors apart from unreliable ones. This information highlights the complex interdependencies woven within SC dynamics, where various variables interact to affect results. The difficulties the models face in this area highlight the challenge of including such dynamics in predictive frameworks.

This analysis shows an information method to integrate simulation and ML. As a fully digital approach, it can be iterating various scenarios. Adopting a data-driven approach because of developing bias-free ML models will make decision-making more results-oriented. The model utilizes data that does not require any expensive data acquisition system; therefore, this kind of approach can be easily implemented. Intelligent decision-making is necessary to develop resiliency in the PFSC. Thus, digital twins are helpful to prospect scenarios.

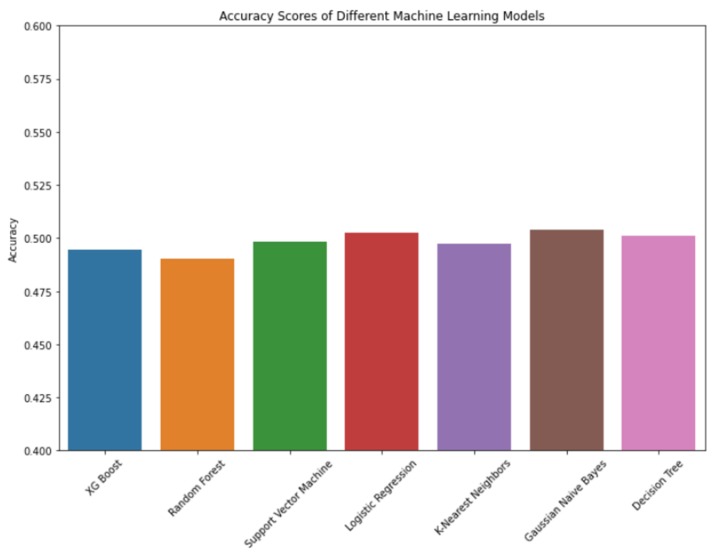

Figure 5. Machine Learning Models accuracy comparison

5. Conclusions and Future Research Opportunities

This research paper presents an innovative approach to evaluating SC resilience and predicting supplier reliability using simulation and ML techniques. The simulation-based assessment of the strawberry SC's resilience and the predictive capabilities of ML models offer valuable tools for SC managers to enhance performance and adapt to dynamic SC environments. The research contributes to the growing body of knowledge on SC management and lays the foundation for further advancements in SC resilience analysis and prediction.

This research paper presents a novel and comprehensive approach to evaluating SC resilience and predicting supplier reliability in the context of the strawberry SC for perishable food. The findings of this research have significant implications for SC management and decision-making. By predicting supplier reliability, the study demonstrated the profound impact of supplier shutdowns on the SC's overall performance. The ML models developed in this research can be integrated into SC management systems to provide real-time predictions of supplier reliability. The performance of suppliers can be appropriately evaluated based on predefined metrics, which include on-time delivery, quality and reliability scores, and other factors depending on the specific industry. This can help SC managers make informed supplier selection and risk management decisions.

Through dynamic modeling of interactions between producers, suppliers, and warehouses, the research highlighted the crucial role of reliable suppliers in maintaining the SC's functionality during adverse events. By simulating different scenarios, the research will help identify the SC's vulnerability to external factors, enabling SC managers to implement contingency plans and strengthen the SC's resilience. This helps SC managers make informed decisions, anticipate potential challenges, and implement appropriate measures to ensure the smooth functioning of the SC, even during disruptive events. With this predictive capability, SC managers can take proactive steps, such as identifying alternative suppliers or adjusting inventory levels, to mitigate the impact on the SC when potential supplier shutdowns are predicted. This model demonstrated its potential for supplier reliability prediction, offering a powerful tool for SC decision-making. Additionally, the Gaussian Naïve Bayes and Logistic Regression models showed promising performance, providing choices for prediction tasks, further enhancing the versatility of the approach.

The ability to predict supplier reliability allows for proactive decision-making, reducing the overall risk and impact of supplier shutdowns on the SC. By combining simulation-based assessments and ML predictions, this research contributes valuable insights into improving SC management in the context of perishable goods and supplier reliability. While every effort has been made to design a comprehensive and robust research methodology, certain limitations are acknowledged. The primary limitation is the reliance on simulated data, which may not perfectly represent the real-world complexities of the strawberry SC. Supplier reliability scores are assumed to follow previous trends, which may only partially capture some variations in supplier performance.

Additionally, the accuracy of the predictive model may be affected by the quality and quantity of historical data available for training. Despite certain limitations, such as data availability and complexity, this research is an essential steppingstone toward better SC resilience and efficiency. Overall, this research's contribution to the field lies in its innovative and holistic approach to evaluating SC resilience and predicting supplier reliability, paving the way for enhanced management strategies and strengthened SC systems in the perishable food industry.
Future research could focus on enhancing model characteristics for training, improving the ML model accuracy, and exploring advanced techniques like ensemble learning, deep learning, and reinforcement learning. Incorporating real-world data from PFSCs like strawberries could enhance simulation and ML models for improved accuracy in specific scenarios. Moreover, integrating these models into a comprehensive framework considering multiple objectives such as cost, lead time, and supplier reliability could enable dynamic SC optimization, facilitating robust and efficient designs. Extending research to collaborative SC resilience and its interactions among multiple entities could offer valuable insights for industries with complex SC structures.

Acknowledgments
The authors want to acknowledge the Mitacs Globalink program for providing funding to the first author.

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