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A preliminary implementation of a retrofitted AI demand forecasting system for Digital Twin-based production scheduling in the food sector

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Abstract—The food industry is increasingly focused on enhancing demand forecasting tools to align production with consumer needs better while minimizing waste. This study investigates the integration of Artificial Intelligence (AI) and Digital Twin (DT) technologies to improve decision-making flexibility in the food sector. Specifically, a demand forecasting tool utilising a continuous XGBoost algorithm was developed, serving as the input for a Digital Twin system designed for a real Italian company in the fresh fruit production scheduling sector. The forecasting system operates in a feedback loop where the forecasted demand is compared with actual orders, enabling real-time production re-scheduling. The results highlight the potential of AI and DT technologies, combined with retrofitting and adaptive correction, to drive continuous optimization of the decision-making process for sustainability.

Keywords—Digital Twin, demand forecasting, food, data-driven, retrofitting system

I. INTRODUCTION

The food processing industry faces significant challenges in achieving sustainable production, particularly when dealing with food waste, which affects economic, social, and environmental sustainability in alignment with the 17 SDGs of Agenda 2030 [1]. To address these challenges, the integration of Artificial Intelligence (AI) and Digital Twin (DT) systems is in increasing application in the food industry to promote sustainability, efficiency, and real-time adaptability in manufacturing processes. Within this context, the transition from Industry 4.0 to Industry 5.0 emphasises the need for more flexible and sustainable work environment [2]. Despite advancements in AI and DT applications, a critical gap remains in integrating AI-based demand forecasting within DT systems for real-time adaptive production planning in the food industry. Existing approaches often treat forecasting and simulation as separate layers, limiting their impact on decision-making and responsiveness. The present study thus proposes a data-driven forecasting framework based on the XGBoost algorithm for the prediction of fresh fruit demand. This forecast is integrated into a DT system that enables dynamic scheduling and adjustments by comparing predicted values with actual orders. Through a retrofitting feedback mechanism, the system also enhances production flexibility and responsiveness. The remainder of the paper is organized as follows: Section 2 discusses the literature review, Section 3 describes the proposed methodology and preliminary application while discussion and conclusions are provided in Section 4.

II. STATE OF THE ART

The literature review explores the key research and applications in AI-driven forecasting DT systems in the food sector (Fig. 1). As consumer demand for higher-quality food rises, accurate demand forecasting become critical for production scheduling and waste minimization [3].

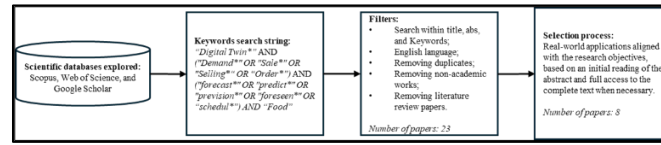


Fig. 1. Literature review process

In this regard, AI techniques and ML algorithms, such as XGBoost, Long Short-Term Memory (LSTM) networks, and Random Forests (RF), are used to enhance demand forecasting and food quality management [4], [5]. For instance, [6] developed four ML-based demand forecasting models specifically designed to reduce food waste. However, many stakeholders within the industry reported challenges in accurately predicting consumer demand, thus complicating the decision-making process [3]. In this regard, integrating demand forecasting models with DT technologies is a valuable solution to address this need. In particular, the DT is a virtual replication of physical systems that allows real-time monitoring, simulation, and optimization of processes, efficiency, and sustainability [7]. For example, [8] proposed a DT model to improve process performance but focused on operational aspects without integrating forecasting tools for production.

Emerging literature demonstrates a positive trend in integrating DT with ML technologies to enhance decision-making in the food industry. However, a significant need is identified in forecasting solutions integrated into DT frameworks for production planning optimization [3]. An in-depth exploration of real applications integrating forecasting models and DT technology in the food sector is, in fact, presented in Table I, showing the following research gaps:

- Demand variation is a major cause of food waste [14], however most studies use DT for production optimization without demand forecasting (e.g., for retails [4]).
- Many studies combining DT with predictive analytics focus on production scheduling, quality control, or food safety [9], [10].
- While some studies integrated AI and ML within DTs, most of them focused on internal factors (e.g., microclimate, energy usage). For example, [3] employed deep learning for crop growth predictions without addressing external demand fluctuations.
- The concept of a DT with feedback loops for continuous production scheduling, remains underexplored in the food sector. Expanding the search string in Fig. 1 including the term “feedback” and synonyms, only one relevant paper is achieved but it is a literature review[11].

The system proposed in this paper aims to fill these gaps by offering a fully demand-informed decision-making framework by combining four key elements rarely found together in the existing literature: (i) the use of XGBoost with continuous retraining and data standardization to address concept drift and demand variability (i.e., variations in data due to the consumer's change in consumption patterns, influenced by meteorological or other factors [12]), (ii) the integration of demand forecasting directly into the DT to guide production decisions, (iii) the inclusion of an adaptive correction mechanism based on the Tracking Signal (TS) to ensure forecast stability, and (iv) the implementation of a feedback loop for real-time reconfiguration of workloads in response to deviations. This integration is in alignment with the Industry 5.0 requirement for more adaptable systems.

TABLE I. REAL APPLICATIONS INTEGRATING DATA ANALYTICS AND DIGITAL TWIN SYSTEMS

Food literature applications	Details on Digital Twin and predictive analytics		
	Digital twin	Predictive analysis	Methodology
[1]	Supply Chain Management, SCM	Logistics efficiency	Diffusion model
[2]	Supply Chain Management, SCM	Logistics efficiency	Time-series forecasting
[3]	Supply Chain Management, SCM	Energy Management and Production	Deep Learning and Cyber-Physical Systems
[4]	Supply Chain Management, SCM	Sales and Operation Planning	Digital Twin
[5]	Supply Chain Management, SCM	Yield production	Machine Learning and graph neural networks
[6]	Process Optimization	Manufacturing Efficiency and Sustainable Production	SuperPro Designer
[7]	Quality Control and Process Optimization	Shelf-Life Prediction and Preventive Maintenance	Model Order Reduction, Machine Learning, Virtual Sensor.

Food literature applications	Details on Digital Twin and predictive analytics		
	Digital twin	Predictive analysis	Methodology
[8]	Quality control	Shelf-Life Prediction	Physics-based modeling and Monte Carlo simulations.

III. RESEARCH APPROACH AND APPLICATION

The proposed methodology integrates an AI-based demand forecasting algorithm with a DT system, establishing a dynamic interface between real operations and the virtual model through a real-time control architecture. The approach proposed was tested at Sant'Orsola, an Italian company operating in the small fresh fruit sector, which manages four production lines and relies on demand forecasts and the simulation tools for production planning and waste reduction. The framework in Fig. 2 is structured as a closed-loop system: Real-time operational data including orders and sales are continuously collected by the company's data infrastructure. These inputs feed a forecasting module based on the XGBoost algorithm, enhanced with daily retraining, continuous standardization, and an adaptive correction mechanism based on TS values. The forecasted value is then sent to the digital twin, which simulates production scenarios and supports planning decisions. A central control unit then compares forecasted and actual demand. If the deviation is significant and falls outside acceptable thresholds, the system triggers a real-time reconfiguration of the production workload. This mechanism ensures that operations remain aligned with actual demand conditions. The resulting information is fed back into the system, completing the feedback loop and supporting continuous learning. Deeper details on the development process are provided in Section A.

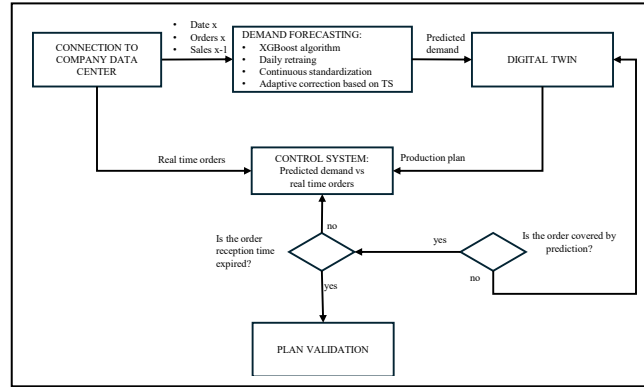


Fig. 3. Research approach

A. Company data center and analytics

The data collected by the company data center are summarized in Table II. Data pre-analytics highlighted key insights into seasonal peaks, fluctuations, and weekly patterns.

Demand is higher in the summer months and lower in winter, with notable fluctuations during the same season, such as between April and May. Weekly patterns show the lowest sales on Saturdays (734 units on average), the highest on Thursdays and Fridays (~4000 units), and stable demand on other days (~3000 units). There is a +27% increase in sales in year X compared to the previous one. Data gaps in key variables like prices and promotions have been identified, but efforts should still be focused on reducing the current forecast error of 109 percent in production scheduling. Four distinct database structures are also tested through an iterative and prototypical process, where each iteration is built on the previous one for refinement (Fig. 3) based on the Key Performance Indicators (KPIs) in Table III [19][20]. The common data among the different databases includes orders and sales data, calculated as follows:

$$Orders = \sum_{i=1}^{x-1} Q_i \quad (1)$$

$$Sales = \sum_{i=1}^x Q_i \quad (2)$$

In particular, (1) is the quantity of orders received before the delivery date x, while (2) is the quantity of orders scheduled for delivery day x.

Database (i) represents data with rows corresponding to specific days of a given year, to organize the data by both time (specific year) and daily attributes. Structure (ii) organizes instead data based on the day of the year across multiple years as follows:

$$Q_{ref,period} = (Q^{X-3}, Q^{X-2}, Q^{X-1}, Q^X) \quad (3)$$

Equation (4) represents sales or orders for the current period X and the previous three years (X-3, X-2, X-1). In structure (iii), each term represents the sales or orders for a specific weekday across four consecutive years. This allows for easier comparison of sales trends for the same weekdays in different years. The organization is expressed as follows:

$$Q_{week,day} = (Q_{week,day}^{[X-3]}, Q_{week,day}^{[X-2]}, Q_{week,day}^{[X-1]}, Q_{week,day}^{[X]}) \quad (4)$$

TABLE II. COMPANY DATA CENTER

Data columns	Data information	
	Description	Value
Year	Code of the year	[X; X-1; X-2; X-3; X-4]
Season	Corresponds to periods: [01/12–29/02; 01/09–30/11; 01/03–31/05; 01/06–31/08]	[1; 2; 3; 4]
Week num	Week number within the year, starting from January 1st	Integer number
Month	The month corresponding to the date	Integer number
Period	Week of the month	[1; 2; 3; 4]
Weekday	Day of the week, starting from Sunday.	[1; 2; ...; 7]
Working day	Indicating working day	[0; 1] (0 = non-working day; 1=working day)
Day	Day of the year	Integer number
Month day	Day of the month.	Integer number
Orders	$Q_{received}(x)$	Integer number
Sales	Target variable: $Q_{actual}(x)$	Integer number

i)	Year	Season	Month	Week	Weekday	Working day	Orders	Sales
	0	4	1	1	4	1	772	1001
	0	4	1	1	5	1	713	1308

Year X-3								
Date	Ref	Month	Week	Annual day	Weekday	Working day	Orders	Sales
01/01/2020	0	1	1	1	4	1	772	1001
02/01/2020	0	1	1	2	5	1	1056	1308

Year X-2								
Date	Ref	Month	Week	Annual day	Weekday	Working day	Orders	Sales
01/01/2019	0	1	1	1	4	1	772	1001
02/01/2019	0	1	1	2	5	1	1056	1308

Year X-1								
Date	Ref	Month	Week	Annual day	Weekday	Working day	Orders	Sales
01/01/2018	0	1	1	1	4	1	772	1001
02/01/2018	0	1	1	2	5	1	1056	1308

Year X								
Date	Ref	Month	Week	Annual day	Weekday	Working day	Orders	Sales
01/01/2017	0	1	1	1	4	1	772	1001
02/01/2017	0	1	1	2	5	1	1056	1308

Fig. 4. Database structures tested

TABLE III. KPIs FOR EVALUATING DEMAND FORECASTING MODELS

KPIs	KPIs information		
	Description	Maximum Acceptable Value	Details
Extra hours	Maximum extra time that the production line can run per day to address forecast errors.	+/- 1 extra hour per line/day	Production flexibility allows for an extra 1,200 units per day (+/- 1 hour at 300 units/hour).
MAPE	Measures the accuracy of forecasts based on the mean absolute percentage error.	20%	MAPE indicates how much the forecast deviates from actual demand. The lower the better.
Tracking Signal (TS)	Indicates a systematic bias comparing the cumulative forecast error to the mean absolute deviation.	Range: [-6, +6]	A value below -6 indicates systematic under-forecasting; above +6 indicates systematic over-forecasting.
Training time	The time required to train a model on a given database.	Shorter time is preferred	Faster training times are prioritized for efficient, frequent updates and retraining.
Inference time	The time required for a trained model to make	Shorter time is preferred	Lower inference times help make real-time predictions

KPIs	KPIs information		
	Description	Maximum Acceptable Value	Details
	predictions on new data.		and adjustments more quickly.

Lastly, in structure (iv), the rows represented specific days of a year, like the previous structure, but with additional columns. These include “Sales day $_{-6}$ ” to “Sales day $_{-1}$ ” to capture recent weekly trends and the “3 years weekday average” column to track historical yearly demand patterns as in (5):

$$3 \text{ yrs weekday average} = \frac{1}{3} \sum_{i=1}^3 \text{Sales}_{\text{Week, Day, Year}-i} \quad (5)$$

Each database was also tested with varying column configurations, incorporating moving averages (MA_t) or Cycle Encoding for seasonality, lag features (Lag_k) for temporal patterns, and binary variables ($Binary_y$) for categorical encoding.

B. Demand forecasting

Approximately 200 tests were conducted through an iterative and prototypical process to select the proper algorithm and features of the forecasting module. The preliminary selection of the demand forecasting began by evaluating statistical and machine learning models tested on the database structure (i) as described in Fig. 5. Among ML models, three algorithms were tested based on their effectiveness in demand forecasting according to [13], [14], [15], [16]. Linear Regression was unsuitable due to non-linearity, while LSTM required long training times.

Gradient Boosted Trees (GBT) thus emerged as the most efficient and accurate model. However, challenges in forecasting low-demand days and the lack of data (e.g., promotions) limitate the model. Daily training and test on (ii) helped reduce error gaps caused by unexpected demand spikes. The second step led to significant improvements, though some noise persisted in the results. The model occasionally underestimated demand due to unexpected sales peaks and orders in year X, leading to high errors in initial predictions and affecting subsequent forecasts. However, the daily retraining process allowed the model to make self-corrections, thus resulting in acceptable KPI values. In addition, deeper analysis revealed overfitting due to the high influence of orders on predictions rather than the day of the week. Testing different adjustments and removing orders led to an increase in forecast performance. Then, tests on database (iii) using the daily GBT model improved in the tracking of weekly demand fluctuations. In the final phase, database (iv) was used to simultaneously capture historical seasonality and recent sales trends. XGBoost, with continuous standardization and daily retraining, was then selected as the best-performing model due to its scalability, computational efficiency and forecasting accuracy.

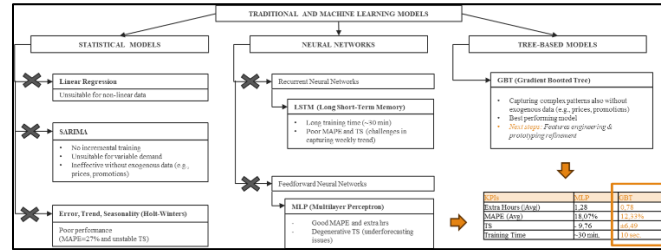


Fig. 5. Preliminary model selection process tested

However, when including order data, TS values fell outside the acceptable range likely due to the absence of complementary information such as promotions or marketing events, which may lead to overestimations as order quantities increase.

To address this limitation, while still leveraging the predictive strength of the forecasting model selected through a rigorous process, a control mechanism based on TS monitoring was introduced. Specifically, when TS values approached critical thresholds, indicating consistent over- or under-forecasting (as shown in Table III), a corrective adjustment of $\pm 10\%$ is applied to the forecast to prevent the accumulation of systematic errors and ensure robust long-term reliability. An example of the resulting demand forecast is presented in Fig. 6, which also highlights an anomaly that may require adjustment and effective management through the DT system.

C. Digital twin

The goal of the DT system is to assist company managers in optimizing production activities. The system should be able to access real-time data from the company’s physical operations, such as past sales figures, warehouse inventory levels, and the status of production lines. The demand forecast will then be used to optimize production line organization through the digital model. Initially, the DT will serve as a planning tool, and over time, by continuously monitoring the real system, it will verify the correct execution of tasks and, when necessary, suggest corrective actions. The modeling and simulation within the DT framework focus on replicating the real-world system’s behavior as accurately as possible. To achieve this, researchers employ advanced simulation techniques tailored to the system’s specific features.

The DT operates as a software tool installed on a desktop PC and connected to the company's system, which is referred to as "Native". It consists of two main parts: the backend, responsible for handling simulations and DT use cases, and the frontend, which provides the user interface (UI). The Native UI enables users to access DT functions based on their authorization level, thus enabling full utilization of the system's capabilities.

In the current case study, the DT connects Sant'Orsola's ERP, MES, and PLC systems via an MQTT Broker, transferring output data. Unlike the Native UI, the On-Premise UI is browser-based and has fewer restrictions, while the Cloud UI, used for external access, has more limitations compared to the On-Premise version. Communication between cloud, On-Premise, and native systems occurs via an external database. In the system modeling phase of the Sant'Orsola project, Discrete Event Simulation (DES) is used to replicate the company's physical structure.

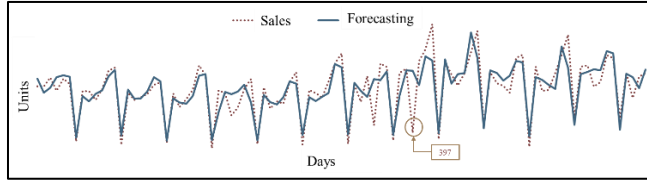


Fig. 6. Demand forecasting with anomaly highlighted

Entities such as pallets, crates, and punnets, each with specific attributes like weight and quality, are modeled. Operators are treated as renewable resources, while items like crates and labels are considered non-renewable.

The simulation, developed using Python and the SimPy library, creates a digital replica of the production line, modeling various stations, from input and output to complex process stations like the Scale station, which checks if punnets meet weight specifications. The conveyor system is also simulated, including tasks along it.

This modular approach allows the digital twin to accurately simulate the real-world production line, enabling precise analysis and optimization. As highlighted in Fig. 2, the forecasted demand acts as the initial link between the real system and the DT. This integration enables DT to acquire key information from departments like sales, inventory, and production planning.

Based on the forecast, the DT sets parameters for the digital production lines, ensuring that the virtual model aligns with expected real-world conditions. This prepares the system for optimized production, adjusting line configurations and resource allocation according to the anticipated demand.

The seamless integration of this system forms the foundation for real-time monitoring and continuous improvement throughout the production process, ensuring efficient resource management. For example, if the forecasted production demand was 3,200 units, producing this amount on a single line would require 9.6 hours, exceeding the standard 8-hour shift by 1 hour and 36 minutes. As a result, two production lines would be activated to meet the demand. The forecast, based on actual sales of 3,100 units, had a mean absolute error of 100 units. This error led to an additional 50 units per line, requiring 10 extra minutes of production per line. In cases of underestimating demand, the benefit lies in reducing operational costs and allowing operators to focus on quality control and preparation for the next day's production.

D. Control system

The DT system is also designed to provide real-time monitoring and optimization. It interacts with the physical asset by implementing strategic optimizations that reflect the system's specific needs and characteristics. The DT system plays a vital role in managing forecasting errors by enabling real-time adjustments to production lines. It creates buffer time to handle forecasting errors, using flexible labor hours to adapt to discrepancies.

If the forecast exceeds actual sales, the system adjusts production by reducing working hours or workforce capacity. Contractual flexibility, which allows for an additional +/- one hour of labor (about 300 units), helps the system better align production with actual demand. For example, in the case shown in Fig. 6, there was a significant overestimation. The forecast predicted 1,390 units, but actual sales were only 397 units on that day. This discrepancy was due to an anomalous sales drop, as historical data from previous weeks and years showed significantly higher sales on similar days (1,432 and 1,805 units), with an average sales figure of 1,457 units. This highlights the challenge of accurately coping with irregular sales patterns.

In this case, initially, production will probably be set higher based on the forecast, but as the actual sales data is received and discrepancies are identified, the DT system will reduce production output if sales remain lower than expected.

This dynamic adjustment will minimize overproduction and waste while ensuring the system is adaptable to fluctuations in demand, maintaining efficient operations even in the face of unexpected sales changes.

E. Results

TABLE IV. SUMMARY OF MODEL EVALUATION AND PERFORMANCE

Evaluated aspects and outcomes	
--------------------------------	--

Performance summary	Challenge or metric	Mitigation strategy / Performance achieved
Forecast performance	Unexpected sales peaks	Impact mitigated after two training iterations: stable response to anomalies.
	Weekly demand pattern	Fully captured.
	Overfitting to order data	Mitigated using weekly-based structure to reduce dependency on order quantity.
	Forecast error reduction	- 89% compared to initial baseline.
	TS without the control mechanism	Ranged between -4 and +10, indicating persistent over-forecasting bias.
	TS with the control mechanism	Ranged between -4 and +6.5, indicating no persistent over- or under-forecasting bias.
	MAPE	Reached 14%, well below the 20% threshold.
	Forecast stability	Ensured by a TS-based adaptive correction mechanism.
	Forecast drift and variation	Handled daily retraining, TS monitoring, and DT feedback; no drift observed.
	Maximum deviation from prediction	+993 units overestimated during anomaly (+3.31 hours).
Efficiency	Average extra working time	1 extra absolute working hour on average; within operational tolerance.
	Training time	10 seconds per model; supports frequent model updates.
	Inference time (including re-training)	~10 seconds total; enables near real-time responsiveness.
Operational Impact	Max DT scheduling error	One extra line activated due to +993-unit overestimation; adjusted via retrofitting.
Scalability	System scalability	Framework designed for extension to other products and production lines.

IV. DISCUSSION AND CONCLUSIONS

The case study on raspberry production in Italy demonstrates the potential of integrating AI-driven demand forecasting with DT systems and retrofitting strategies to optimize production scheduling and reduce waste. Using the continuous XGBoost algorithm applied to a week-based database, the model achieved an 89% reduction in forecasting error over a three-month horizon. This improvement was largely due to the model's capacity to capture seasonal patterns and account for anomalies such as promotion-driven sales peaks, which were previously overlooked.

This forecasting adaptability reflects the system's ability to manage concept drift. Although no separate drift detection algorithm is used, the model incorporates a daily retraining routine and continuous standardization, ensuring that the most recent patterns are consistently learned. Moreover, the adaptive control on the TS enables the model to correct for persistent over or underestimation trends, limiting error accumulation without external triggers. While no explicit alarm is currently raised in the case of large consecutive variations, this is mitigated by the combined effect of retraining, TS monitoring, and the feedback loop. The new forecasting tool also enhanced operational responsiveness, enabling real-time adjustments based on actual demand. By incorporating a feedback-driven system, the company can progressively align production with market needs, reducing discrepancies between forecasted and observed demand.

While this work presents a preliminary implementation, the retrofitting system, already tested, will play a central role in future model refinement. Following complete real-world deployment and structured feedback from the company, future research will assess the effectiveness of this feedback-driven approach by comparing closed-loop, semi-open, and open-loop configurations in real

production settings, with a particular focus on perishable goods. A future enhancement may also include an alert function within the DT to signal when unusual variation patterns require manual model inspection.

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REFERENCES

- [1] Y. Tang, H. He, Y. Wang, and Y. Wu, "Using a Diffusion Model for Pedestrian Trajectory Prediction in Semi-Open Autonomous Driving Environments," *IEEE Sens J*, vol. 24, no. 10, pp. 17208–17218, May 2024, doi: 10.1109/JSEN.2024.3382406.
- [2] T. Y. Melesse, M. Bollo, V. Di Pasquale, and S. Riemma, "Digital Twin for Inventory Planning of Fresh Produce," *IFAC-PapersOnLine*, vol. 55, no. 10, pp. 2743–2748, 2022, doi: 10.1016/j.ifacol.2022.10.134.
- [3] G. Hu and F. You, "AI-enabled cyber-physical-biological systems for smart energy management and sustainable food production in a plant factory," *Appl Energy*, vol. 356, p. 122334, Feb. 2024, doi: 10.1016/j.apenergy.2023.122334.
- [4] S. Sengupta and H. Dreyer, "Realizing zero-waste value chains through digital twin-driven S&OP: A case of grocery retail," *Comput Ind*, vol. 148, p. 103890, Jun. 2023, doi: 10.1016/j.compind.2023.103890.
- [5] K. R. Chaganti, B. N. Kumar, P. K. Gutta, S. L. Reddy Elicherla, C. Nagesh, and K. Raghavendar, "Blockchain Anchored Federated Learning and Tokenized Traceability for Sustainable Food Supply Chains," in *2024 4th International Conference on Ubiquitous Computing and Intelligent Information Systems (ICUIS)*, IEEE, Dec. 2024, pp. 1532–1538. doi: 10.1109/ICUIS64676.2024.10866271.
- [6] A. Koulouris, N. Misailidis, and D. Petrides, "Applications of process and digital twin models for production simulation and scheduling in the manufacturing of food ingredients and products," *Food and Bioproducts Processing*, vol. 126, pp. 317–333, Mar. 2021, doi: 10.1016/j.fbp.2021.01.016.
- [7] T. Eppinger, G. Longwell, P. Mas, K. Goodheart, U. Badiali, and R. Aglave, "Increase food production efficiency using the executable Digital Twin (xDt)," *Chem Eng Trans*, vol. 87, pp. 37–42, 2021.
- [8] J. Schemminger, S. Raut, B. Sturm, and T. Defraeye, "A hybrid digital shadow to assess biological variability in carrot slices during drying," *Thermal Science and Engineering Progress*, vol. 50, p. 102507, May 2024, doi: 10.1016/j.tsep.2024.102507.
- [9] T. Y. Melesse, V. Di Pasquale, and S. Riemma, "Recent Advances of Digital Twin Application in Agri-food Supply Chain," 2024, pp. 147–157. doi: 10.1007/978-3-031-24771-2_13.
- [10] G. P. C. Tancredi, E. Bottani, and G. Vignali, "Digital twin-enabled process control in the food industry: proposal of a framework based on two case studies," *Int J Prod Res*, vol. 62, no. 12, pp. 4331–4348, Jun. 2024, doi: 10.1080/00207543.2023.2260495.
- [11] J. Qiao, M. Zhang, L. Qiu, A. S. Mujumdar, and Y. Ma, "Visual early warning and prediction of fresh food quality deterioration: Research progress and application in supply chain," *Food Biosci*, vol. 58, p. 103671, Apr. 2024, doi: 10.1016/j.fbio.2024.103671.
- [12] A. Azeem, I. Ismail, S. M. Jameel, and K. U. Danyaro, "Transfer-learning enabled adaptive framework for load forecasting under concept-drift challenges in smart-grids across different-generation-modalities," *Energy Reports*, vol. 12, pp. 3519–3532, Dec. 2024, doi: 10.1016/j.egyr.2024.09.040.
- [13] C. Ingle, D. Bakliwal, J. Jain, P. Singh, P. Kale, and V. Chhajed, "Demand Forecasting : Literature Review On Various Methodologies," in *2021 12th International Conference on Computing Communication and Networking Technologies (ICCCNT)*, IEEE, Jul. 2021, pp. 1–7. doi: 10.1109/ICCCNT51525.2021.9580139.
- [14] K. Wanchoo, "Retail Demand Forecasting: a Comparison between Deep Neural Network and Gradient Boosting Method for Univariate Time Series," in *2019 IEEE 5th International Conference for Convergence in Technology (I2CT)*, IEEE, Mar. 2019, pp. 1–5. doi: 10.1109/I2CT45611.2019.9033651.
- [15] N. G. Paterakis, E. Mocanu, M. Gibescu, B. Stappers, and W. van Alst, "Deep learning versus traditional machine learning methods for aggregated energy demand prediction," in *2017 IEEE PES Innovative Smart Grid Technologies Conference Europe (ISGT-Europe)*, IEEE, Sep. 2017, pp. 1–6. doi: 10.1109/ISGTEurope.2017.8260289.
- [16] S. K. Panda and S. N. Mohanty, "Time Series Forecasting and Modeling of Food Demand Supply Chain Based on Regressors Analysis," *IEEE Access*, vol. 11, pp. 42679–42700, 2023, doi: 10.1109/ACCESS.2023.3266275.