A Survey on Digital Twins to Track Food Quality

Galiveeti Poornima
Networks and IoT Lab,
School of CSE, Presidenc University,
Bengaluru, India.
https://orcid.org/0000-0003-4289-114X

Sukruth Gowda M A
Big Data Analytics Lab,
School of CSE, Presidenc University,
Bengaluru, India.
sukruthgowda@presidencyuniversity.in

***Abstract*—Making materials into finished items is extremely complex due to the multiple chemo-physical, biological, and physical properties that must be controlled all through the food production cycle. Production must also modify processes to account for the ingredients' variability, for instance when the raw material's quality materials varies seasonally. "Digital twins" are a modelling, simulation, and optimization method that may be used for a variety of processes in the context of Industry 4.0. The concept of a "digital food twin" and how it can benefit the food business are described in this vision paper. A digital twin must consider not just the processing steps as well as the biochemical, physical, or microbiological elements that affect the meal by themselves because the raw components can vary. after processing is complete. Using a method known as food processing modeling and simulation, we will demonstrate a hybrid modeling technique in this study that integrates the traditional model and simulation of the physical and biochemical elements of food. a machine learning-based, data-driven technique that analyzes the data. This study offers a conceptual framework for our idea of a digital twin based on wearable gadget technology and artificial intelligence that is understood. Four separate case examples are used to discuss the possibilities, and open research projects are derived.**

***Index Terms*—digital twin, food processing, Industry 4.0, artificial intelligence, machine learning, self-aware computing systems**

I. Introduction

The suppliers and agri-food production lines are currently not moving quickly enough to meet the goals for sustainable development. They fall short of their most basic goal of providing nutritious food to a growing global population, leaving 940 million of people undernourished. They broke some of the alleged limitations of the earth, were expensive and polluting, and failed on a number of other fronts as well [1].

A common solution is transformation through improvements in digital technology [2], [3]. Such recommendations strongly favor computer-enabled technologies, including embedded systems, intelligent sensors, and artificial intelligence (AI). Here, despite its potency and expanding adoption across industrial domains, we examine this same potential of the digital twin (DT) technology, that has not yet been considered for boosting the sustainable development of the agro - based sector, particularly across mitigating malnutrition and undernutrition, reducing greenhouse gas (GHG) emissions, and attempting to prevent food waste. The factors that could hinder the virtual agrifood supply chain from reaching their full potential are then discussed, both enabling and obstructing factors.

With the growth and digitization of the industry toward Industry 4.0, the concept of creating digital copies of physical equivalents hit the market. [4]. The food business is of particular relevance since it necessitates a high level of resource efficiency [5]. Agricultural systems have evolved over time alongside technological developments, enabling growth in productivity, product diversification, food stock resilience, and international trade. However, despite these advancements, food systems continue to face impossibly severe challenges on a global scale. Changing climate, the requirement to feed an growing worldwide population, and increasing global food waste are just a few of the problems that pose a severe danger to today's food systems. Additionally, societal demands for increased food sustainability, traceability, and provenance are rising chains of virtualized agri-food value [6].

A key element of Industry 4.0 is the digital twin, a digital version of a process or product created with data received by sensors to enable simulation or actual evaluations of a production status [4], [7]. The use of digital twins inside the food industry appears useful for a variety of reasons. The COVID-19 epidemic brought to light the food supply's vulnerability [8]. Food manufacturing techniques must allow for significant levels of adaptability and flexibility [9]. Different input material quality levels also have an impact on the quality of the final output. A change in production process parameters is necessary, especially when seasonal variations affect the quality of raw materials. A virtual model of an existing product could streamline the introduction procedures of new items. An ego software system uses the digital twin as its knowledge base and may learn the correct production process parameters [10]. In contrast to related technologies of the manufacturing of material items, food production has extra unique requirements [11]. These can't just rely on the processing steps because raw materials can vary greatly, thus they must also take into consideration the food's biochemical, mechanical, or (micro)biological properties. The software can also be used to create an extensive digital supply chain that combines real-time and real-world data, allowing the supply chain to respond to unforeseen occurrences and uncertainties.

II. History

A. Food Distribution

A distribution group is a network of individuals arranged around procedures and processes with the purpose of supplying the market with goods or services in order to satisfy a particular consumer demand. For sustainability-related reasons, this network takes into account user feedback and supply-chain elements such material recycling [15]. The participants in this network are linked by procedures and deeds that result in value in the form of finished commodities or services. [14]. The manufacturing and conversion of raw resources into food items, in addition to their retail and consumption, are all part of food distribution in the same meaning [13]. Due to the complexities of manufacturing, managing, and shipping food goods, food distribution do differ greatly from other networks [16].

We focus on creating a simple, linear, and organized system for distributing meals despite the fact that it is crucial to take into account not just predefined but also the completely irrelevant and supplementary tends to flow that are enclosed within the food distribution because these are chances to reduce food waste and loss through recycling and reuse [12]. Since the focus of this survey is on specific food distribution activities that appear the same in both a simple food distribution and a circular view, this is sufficient. An illustration of the food distribution and the key players to whom the digital twin services will be assigned is shown in Fig. 1. Food is often distributed in a cycle that begins with production on an agricultural farm, continues through supply, manufacture, transportation, and retail, and ends with consumption. It's important to note that the steps could subsequently be split up into several manufacturing or transport sub-entities: Shoji et al. [17], for instance, look into the cold chain of vegetables and fruits from the farm through the storehouse through distribution to the merchant. The supply is transported in two different ways by authors: from the storehouse to the distribution warehouse and from the distribution hub to the retailer. According to our view, the storehouse is a component of the processing step, and distribution would include both transportation and delivery.

Since solutions and mitigation strategies must be devised to stop disturbances to the distribution network, it is essential that distribution networks be designed with these factors in mind [12]. These interruptions have a direct impact on the other actors and the normal flow of the distribution network [18]. Human mistake, misunderstandings in communication, faults in organizational procedure, and issues with the quality of supplied commodities are specifically the food distribution disruptions that occur most frequently [19]. As a result, disruptions could have a severe impact on the end product's longevity, safety, and quality [12], [16].

A number of challenges also arise in the distribution of food at various stages [20]: Production planning in the processing stage addresses comment damage along with requirement prediction. Distribution identifies trip planning, this same forecasting of risks and interruptions in the distribution system, in addition to the forecasting of shelf-life. Production evaluation and optimization within the production stage includes crop safety and security, in addition to livestock control.

B. Concepts Related to Industry 4.0

The fourth revolution is referred to as "Industry 4.0." Cloud technology, computer systems (CPSs), as well as the Internet of Everything are among the technologies it uses (IoT). While "Industry 4.0" is frequently used in Europe, "Industrial Internet of Things" (IIoT) is a term that is more frequently used in the US to describe advancements in big data, cloud computing, and networking of industrial gear and systems. Based on CPSs and IoT [21]. Industry 4.0 production processes, such as logistical, services, and maintenance, are efficiently synchronized [22]. Instead than focusing on a single process or technology, Industry 4.0 combines all processes into a highly customizable and integrated production process. With the implementation of Industry 4.0 or IIoT, the smart factory would be established, which is an integrated manufacturing process that is totally self by the linked machines or smart machines without any human contact. [23].

Additionally, modern food distribution use integrated information and communications technologies (ICT) systems more and more frequently to help with risk and uncertainty mitigation, process improvement, and a variety of other uses [14]. Additionally, traceability and decision-making processes within the food distribution are of special importance for ICT systems [24]. In order to pinpoint issues with food quality and safety and to show the customer and authorities the product's provenance, traceability is crucial [16]. Traceability systems for food distribution, according to Zhong et al. [12], differ significantly depending on geography, laws, and the level of digitization of the distributing food. Inside the food distribution industry, ICT systems acting as digital twins can help with decision-making, cooperation, planning and scheduling logistics and distribution, and warehouse management [25].

III. Digital Twins

A. Definition

A digital twin of a particular product is described as a virtual representation of its physical counterpart that:

1) contains all necessary components, such as all geometrical elements and material properties;
2) simulates all pertinent processes and their kinetics accurately and realistically throughout the product's life-cycle;
3) is linked to the genuine product and processes by sensor information, which would be preferably continuously updated in real-time.

Other names for it include a virtual ghost, synchronized virtual prototype, virtual avatar, and digital shadow. The form, size, and structural components of horticultural output should ideally be included in a digital twin that is part of the agricultural supply chain. (e.g., skin, seed, pulp). Before the advent of digital technology, it was known as virtual fruit. It also

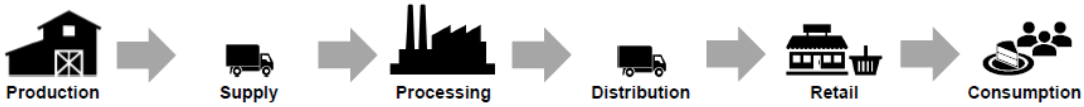

Fig. 1. A structure of Food Distribution as per [12]

replicates the physically, chemically, sanitary, psychological, and developmental states of the product as well as their development all through the cold chain on the basis of collected data about the ambient circumstances (such as surface temperature, humidity levels, and metabolism gas concentration). Fig. 2 depicts the usual processes that can be captured. Fig. 2 shows a digital-twin system for cold chains of horticultural crops. An illustration of this twin is a single horticulture item that is inserted inside a fruit pallet and contains a sensor that gauges the ambient temperature. In order to record the fruit's thermal status, each pallet might contain its digital twin fruit. Then, these twins can detect the well-known variation in fruit chilling between various pallets, such as between the front and back of a refrigerator [26]. It is even possible to create a digital twin for such a full pallet (Fig. 3), however this would require more computational power. Here, for instance, only at the circulating inlet in the pallet, a sensor or maybe numerous sensors could determine the air temperature. Because of the number and diversity of processes taking place within and around the produce, additional surrounding parameters should be sent to the digital twin for improved precision or to measure specific quality traits. (Fig. 2).

A digital twin needs three things to work (Fig. 3):

- A computerized main model of the thing that includes a blueprint for the real thing, its features, and the operations connected to it. In our case, the actual asset is a crop or a pallet of fruit, which is a horticulture product.
- Sensors that measure ambient temperature, relative humidity, oxygen levels, and ethylene in real supply chains.
- Connecting the digital product design is the process to the actual asset using sensor data. The digital twin's relationship to the real-world process distinguishes it from ordinary computational models. The ideal way to establish this connection is during operation, though it is also done gradually offline.

The connection between both the digital master and the actual reality made possible by sensing allows the digital twin to adapt and move with its real-world counterpart during its post - harvest life, from containers to arrival at the retailer. Every every "virtual" product goes through a different evolution. By doing this, the digital twin takes into consideration the distinct boundary circumstances that each product is subjected to. It thus reacts to changes in real life in a realistic manner. Digital twins are therefore especially helpful when every product has a unique and changeable life cycle. In such case, digital twins help tangible assets, like fruits, tell their narrative. Digital twins can be used to forecast how a certain cargo will develop in the future in addition to recognizing current issues and documenting this history through data storage.

B. Digital twins in technology

Different industries have seen the emergence of digital twins [27]. The design, manufacture, and operation of items and processes, these twins frequently assist with maintenance, which includes inspection, repair, and upkeep. Digital twins are therefore used to provide information about items and processes in addition to measurement values. Since there isn't a lot of participant literature on digital twins, we also include links to recent initiatives or online resources below.

Engines, pumps, and turbines are just a few of the devices that have digital twins made for them in aeronautical engineering and allied industries like product manufacturing. NASA used a mirroring technique with Apollo 13 in 1970 as a forerunner to the digital twin to safely return the astronauts. For both its manned and unmanned aircraft, NASA now employs the digital twin concept [28]. There are also efforts underway to create digital twins of complete manufacturing facilities [29], [30]. These twins are built for each item on the assembly line or for various parts of an item, and they are later joined in the actual and virtual worlds. Building information modeling (BIM) has been advocated in the field of building technology as a way to construct cognitive buildings [31]. Digital twins of automobiles are employed in the automotive industry to time maintenance of parts, such as oil replacement [32]. Instead of being determined by miles, maintenance is triggered by the vehicle's history. As a result, maintenance incorporates a high level of individualization, maximizing resources.

Healthcare is a sector where digital twins have a lot of untapped promise [33]. Every human being, every human organ, and thus every matching image twin are special and develop differently over the period of the patient's condition. As a result, there is tremendous potential for this development in digital technology. A digital twin is incredibly beneficial if it can include anatomical or physiological information that is patient-specific. This can be shown, for instance, when a digital model is made utilizing CAD geometries of a specific organ that was acquired via X-ray imaging or MRI for a specific patient [34]. Generic anatomical models of particular organs collected from a large population of patients can be used as an alternative. Because testing therapeutic strategies can occasionally be expensive and risky, with lasting negative effects, it is especially attractive to utilize digital twins to explore "what if" scenarios. Thanks to this technical alternative, in-silico trials can be carried out on a large number of simulated patients before the actual clinical trials. Such digital twins could also serve as a foundation for individualized

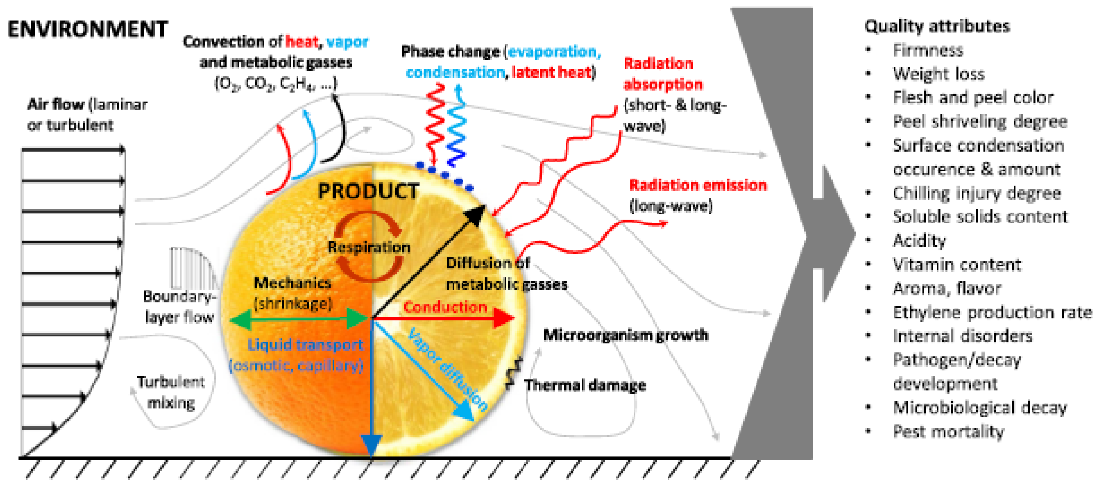

Fig. 2. A mechanistic model must incorporate relevant activities within and around a fruit and a list of key food quality parameters to capture and forecast food quality progression (part of figure of orange fruit: dreamstime.com).

medicine, for instance by merging it into theranostics, in which digital twins can suggest customized treatments by diagnostic procedures or sensing.

Digital twins are used in surgery, among other healthcare settings, to teach surgeons a completely new method. This is accomplished by the use of interactive simulations of the a mechanical material feedback, specifically the tissue response during incisions (e.g., [35], [36]. Digital twins are frequently used in the treatment and therapy of aerosol pulmonary medicine [37], [38]. By employing an implantation that is specifically designed for a given patient, digital twins enable neurosurgeons to better systematize, size, and position the implants throughout this invasive operation again for repair of aneurysms. The application of digital twins for a tailored examination of MRI safety for people with implants [39], photothermal therapy therapy, or targeted ultrasonography for tumor ablation uses the Sim4Life modeling platform [40], which combines sensor feedback. Digital twins are referred to in many smart healthcare applications in a more general sense because not all of them have a strong attachment to sensor data. Instead, using patient-specific information offers them a relationship to the real environment or the real patient, such as tissue morphology from X-ray CT.

In personalized targeted therapy, where these in-silico technologies substantially support in-vitro and also in experimental work, digital twins are anticipated to play a significant role. In this respect, growing usage of genome sequencing of individuals may result in the creation of pharmacological treatments that are specifically tailored to the genetic state of the patient [41]. A major challenge is ensuring the mechanistic models are verified and validated in order to be accepted by regulatory agencies, but there are currently certain standards for theory modeling [42]. Digital twins may also bring up moral concerns, such as patient data security or unfair treatment of individuals with and without digital avatars [43].

C. Facilitators

Digital twins are decades-old. Recent important enablers support the strong expansion of such twins in many industries:

- Miniaturization and lower sensor costs enhance measurement points and spatial resolution.
- Huge quantities of sensor information can be remotely captured and transferred in real time within a network thanks to enhanced connectivity (IoT, cloud) or wireless data transfer (e.g., Bluetooth, LoRa, 5G).
- Computational power, data transfer hardware, and storage systems for digital twins becoming more affordable as a result of cheap cloud services.
- Open data [44], [45] and data standards are being prioritized.
- Simulation software and computer hardware have advanced. Now, millions of degree of freedom complex finite element models may be run in real time and included in user-friendly executable code for physics-based twins. Data-driven twins are able to effectively handle and understand vast volumes of data from contemporary horticulture supply chains for products because to recent advancements in artificial intelligence and machine learning [46], [47].
- New programs for smartphones and tablets provide simple, approachable user interfaces.

IV. Related Work

The usage of digital twins in the food sector, as exemplified by food distribution, is examined in this article, along with the potentials and difficulties that may arise. We give a summary of related publications in the field of digital twins in this section.

There are literature evaluations on digital twins even if the idea of them and their technological potential are still at their infancy. Some reviews, though, were considered for this work even though they weren't specifically about food,

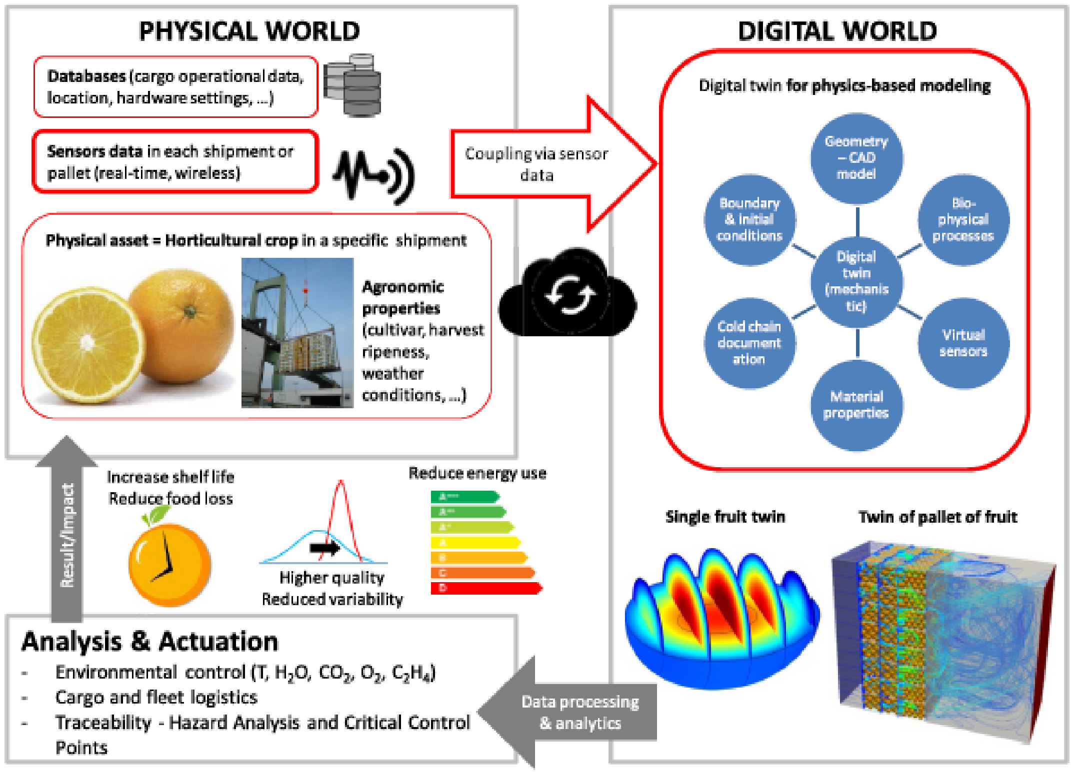

Fig. 3. The structure of a physics-based (mechanistic) digital twin in a fresh horticulture produce delivery chain (picture of orange fruit: dreamstime.com, other portions borrowed from [26].

the meal business, or at least certain aspects of the food distribution. By identifying the core terms of digital twins, Jones et al. [48] described digital twins in general. As a result, they looked at technology applications and usage goals. The authors concluded that a review that was restricted to more unified fields would be preferable after identifying research needs to apply digital twins. Abideen et al. [49] reviewed the literature on ML incorporating digital twins with respect to the distribution networks and logistics. The authors also offer a framework for doing this. However, they don't pay any attention to the food industry or the quality of the food at all; instead, they concentrate on using digital twins to improve logistics. From a social science perspective, digitization in agriculture was examined in Klerkx et alwork .'s [50]. In this context, they examine many associated technologies, including IoT, blockchain, and digital twins, in relation to social factors including the identity and skills of the farmer, ethics in terms of electricity supply and use and data privacy, and economics.

Other works focus on a certain stage of the distribution network. Pylianidis et al. [51] conducted an assessment of the use cases for digital twin adoption across all disciplines and in agriculture in particular. They organized the apps in accordance with the degree of the distributing food and the kind of digital doppelganger, respectively, much like we did in terms of disciplines and services category. They also took into account the TRL, or the ability to distinguish between ideas, models, and operational digital twins. Verdouw et al.'s [52] scheme was also provided, and it is employed in our work. However, they were only concerned with agricultural applications, such as crop management and animal monitoring, which we also covered. The words "digital model," "digital shadow," and "digital twin" are used interchangeably, according to Kritzinger et al. [53], who distinguished the degree of integration regarding the data transfer between both the virtual and physical entities. The type was further considered by the authors in light of the TRL. They demonstrated that digital twins are most frequently used in manufacturing, however the studies did not concentrate on food processing.

The work of Tebaldi et al. [54] provides a more comprehensive picture of the agri-food distribution network, taking into account the SC stages of production, processing, and distribution. We used the apps described there into our work to make it comprehensive. Additionally, the estimation of interruption risks in the works by Ivanov et al. [55] and Burgos and Ivanov [8] considered the complete distribution network. In order to analyze risks, forecast resilience, and optimize the distribution system to prevent catastrophic disruptions, ref. [55] developed a digital twin framework. A digital twin is used to investigate the COVID-19 pandemic's effects on food distribution in [8].

A. Smart food factory

IoT technologies and machine learning algorithms are used in Industry 4.0 to intelligently collect and analyze data [57].

Data sources includes raw material, machine, and customer information (e.g., information about sales or complaints). In particular, machine learning can optimize production planning [58], such as employing genetic algorithms to optimize production step sequence or incorporating photo identification for quality control. Machine predictive maintenance is another example [10], [59]. The procedure and machines are the main focus, though. The food industry's internal operations and product view are excluded [56]. Proactive adaptation forecasts adaption concerns (e.g., by identifying patterns in past data) and prepares or adapts [60]. When a disruption occurs, real-time production site data would enable proactive adaption and dynamic adjustment.

B. Food simulations

Food science typically suggests modeling or simulating food features and traits. We demonstrate application bandwidth below. Myhan, Białobrzewski, and Markowski [61] created a mathematical model of food material rheology. Food matrix affects chemical reactivity, according to [62].Van Boekel proposed using mathematical models to quantify food characteristics including color, nutritional content, and safety [63]. Food industry numerical simulations simulate process or product features.Hartmann simulated high-pressure treatment's thermal and fluid-dynamic effects [64]. Abdul Ghani et al. solved the axisymmetric continuity, momentum, and energy conservation equations to replicate natural convection heating in a can of wet food during sterilization [65].The authors of [66] used finite element analysis to study heat transport into an oxygenated food matrix. The white-box technique of modeling or simulink approaches allows for the extraction and explanation of variable relations. These methodologies always require abstraction from different parts due to the complexity of the modeled components. This limits their productivity. These methods also involve domain knowledge of food attributes and modeling/simulation techniques.

C. Digital twins in food

Digital twins can be imaginary, which simulate reference objects, real-time, predictive, prescriptive, autonomous (using AI), and recollection (with historical data) [67]. Food processing digital twin concepts are few. In a recent analysis [56], we demonstrated that agro- based digital twins were limited to certain features (e.g., animal monitoring, cultivation practices, or hydroponic systems) rather than generally applicable across the value chain. Most methods monitor and some predict. However, few incorporate autonomous control. The poll also found that digital food twins require multidisciplinary understanding, notably in modeling bio-physical processes that affect food qualities owing to raw material heterogeneity. Literature hasn't integrated this. Numerical modeling and data-driven approaches can predict sensory experience of complex foods like yoghurt [68]. This vision study proposes hybrid modeling that adds data to local food models and simulations. The smartFoodTechnologyOWL program examines the applicability of digital twins to food processing [69]. Process mapping improves cyber-physical production system control. They continuously develop a "virtual image" of a product during production to make food quality control safer and more efficient. Other initiatives include physical models to forecast food processing changes. Physical, chemical, and microbial processes are integrated [70]. This form of digital twin frequently lacks a data-driven perspective on processes, thus [70] propose real-time connection of sensor information with the digital twin. That would enable proactive problem-solving. The goal is not to change the production process or predict important occurrences with the data. Digital twins monitor production [71]. Digital twins can combine environment, operational, and process data, while autonomous systems can react to state changes [**?**], [71]. Food process modeling now focuses on optimal design and cost targets, but it could reduce inter-product variability, increase transparency, and save resources [73].

D. Indicators and Sensors

Indicators can identify a substance's existence, reactions, or concentration. Indicators either within or outside the packing change color to indicate analytical results. Indicators vary. Time-temperature indicators, freshness indicators, and gas indicators are the most prevalent varieties. Unlike unchangeable indications, sensors in food packaging or the environment can sense temperature, humidity, pressure on food, and vibrations (accelerometers). Chemical sensors or biosensors monitor CO2 or hydro-sulfuric acid concentrations to determine perishability. Non-dispersive infrared (NDIR) sensors, chemical sensors, electrolytic, ultrasonic, and laser technologies assess oxygen and CO2 concentrations. Biotechnologies use enzymes, antigens, hormones, or nucleic acids as receivers. These identify salmonella, E. coli, and listeria. The authors of [74] presents the latest sensor and indicator types. Sensors enable real-time data collecting for digital twins.

V. Digital Food Twin System Model

In order to close the gap left by the models' abstraction and produce a composite digital food twin for attaining real-time, anticipatory decisions of adaption inside the food supply chain, this paper proposes and explores a notion that supplements the conventional modeling or simulation. As a result, such a concept makes it easier to

i) comprehend how a supply chain behaves,
ii) foresee difficult circumstances, and
iii) decide how to modify the procedures.

A. Data origins

To make sure the chain of custody of the manufacturing and the status of the food, the digital twin is created using artificial intelligence and machine learning from production systems and extra data sources (such as scientific principles, process the data, or input materials data). This allows again for simulation of a variations of the food during process operation.

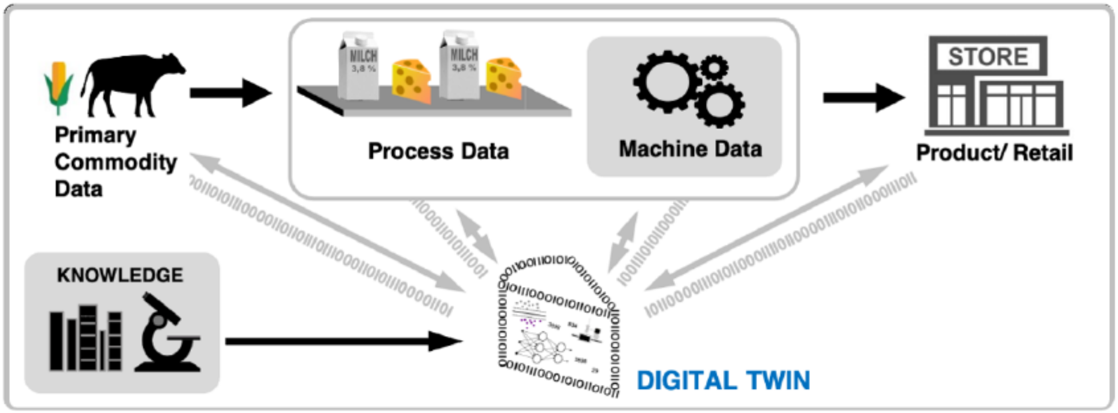

Fig. 4. The digital food twin which integrates the data from various sources.

Fig. 4 depicts how we think about a digital twin. We emphasize the instance of a milk product in the picture and the paragraphs that follow (e.g., cheese). The digital twin incorporates data from raw materials, customer complaints, and expert knowledge in addition to sensor, machine, and processing data from the manufacturing site (such as temperatures, pressure, or pH value) (e.g., about the handling of production issues). The digital twin gives data on the actual food preparation and provides feed back to a food process operation by utilizing various modeling methods based on cytotoxic drugs modeling and simulation studies from the field of food science. These simulations that are based on mathematical models also aid in forecasting how the item will change as a result of the procedures and environmental factors. Forecasts on how various phases in the process can affect the product's quality can be made using this data. As a result, the digital twin is appropriate for both retrospective and analytic applications of the operation and the product's quality.

By using the fermentation of yogurt as an example, we hope to demonstrate the possibilities. It would not be possible to apply the traditional digital twin notion as it is known from Industry 4.0. The production processes are controlled and described using process data, primarily from machines. The state of the product won't change unless the machines take some sort of activity. However, after infection with starter cultures, the fermentation process for yogurt is primarily focused on resting. Because the process takes place inside the product, the data set cannot adequately represent the process. We gain a more accurate representation when we add existing scientific models to the sparse process data to describe the actions of the bacterium. However, the model itself wouldn't be sufficient when starter cultures were injected because the model abstracts so each set of starter cultures has its own variances, much like milk, whose characteristics change over time (due to different feeding). Accordingly, a blend of either is important: both the model to comprehend how the conversion of milk into yogurt functions and the data available to modify the model's parameters. With the concept of the digital food twin, we want to accomplish this.

B. *Analysis*

Deep learning techniques are frequently used to extract information from huge datasets. These methods are incredibly effective and offer a great sense of independence in the learning process. The user is given a black-box and is so unaware of the inner workings. The resulting models, however, are extremely complicated and challenging to understand. Because of this opacity, smart sensors cannot be fully tested before being put to use in useful ways. As a result, combining the derived forecast with the already used food science models is impossible. Therefore, for the purpose of creating the digital twin, we depend on machine learning, particularly those in the area of explainable machine learning.

Machine learning that is explicable and validated systematically with user input is known as explainable machine learning. explainable machine learning is concerned with techniques and algorithms that explain to humans why a choice was made. As a result, the user is included in the machine learning model and has the ability to actively improve the system's quality by using cognitive skills like generalization. With regard to the lack of results that can be explained, explainable machine learning fills the gap between both the great potential of machine learning and its inherent risks.

These comprehensible machine learning techniques assist in converting sensing data into a virtual twin model that can be utilized for simulation. These explainable machine learning models are also explainable, unlike methods based on artificial neural networks (such as deep learning), and people can comprehend and modify them. This makes it easier to incorporate specialized knowledge into the learning process. There are two viable methods for explainable machine learning:

1) Some machine learning algorithms, such as decision trees or random forests, are intrinsically explicable. These may have drawbacks for huge data sets and do not offer automatic feature extraction like deep learning techniques do.
2) The goal is to include a second device called XAI component for non-explainable approaches, like deep

neural networks, which tries to utilize models to explain the outcomes (see Fig. 5).

We aim for the second strategy since the XAI component can be based on the aforementioned food science models and simulations. The second method also uses deep learning techniques, which perform better than conventional machine learning methods. If approaches like random forest can be employed, the first group is preferred since these techniques produce models that can be explained. In general, the choice is based on the use case, the data set at hand (only sizable datasets can be used with deep learning techniques), the effectiveness of the approaches with category 1 explainable models (such as random forest), and whether or not the XAI component can be implemented.

C. Choosing a Model

The creation of a machine learning workflow that enables automatically the pre-processing of data, selection of a machine learning approach, and development of machine learning models is a challenge. The choice of machine learning method is particularly crucial because the data pattern affects how well the method learns. Based on the 1997 "No-Free-Lunch Theorem" [75], which states that no optimization algorithm is best suited for every situation, a comparison to the field of machine learning can be made: no machine learning technique is best suited for every type of data. Based on the properties of the data and the pattern of the data, recommendation systems can assist in selecting the optimal fitting approach and configuring its parameters, or hyper-parameter tuning. We intend to modify and incorporate earlier work on recommendation algorithms for time series forecasting [76].

The preprocessing of the data, or the creation of learning features, is a crucial stage in the information analysis using machine learning. Typically, this task calls for manual labor and subject-matter knowledge. Although deep learning systems automatically do this feature extraction, they have the drawback of having less explainability. The automatic, organized feature extraction from log data is supported by approaches to prediction based on log data. Such methods train algorithms for machine learning using historical event-log data [77]. With log-based predictions, the necessary procedures can be automated but are also well-defined, supporting the data pre-explicability. processing's An strategy for predictive maintenance that incorporates log-based prediction was presented by Gutschi et al. [77]. To affect the likelihood of a critical machine malfunction sufficiently early, Lopez et al. use chronological logs emitted by manufacturing equipment from various industrial factories [78]. We intend to incorporate a comparable log-based prediction to automate the extraction of pertinent data patterns and characteristics from historical data, particularly given that such an approach may improve the generalisability of a digital twin among various food categories.

D. Simulation

The study of machine data is a common emphasis of Industry 4.0 approaches for digital twins, but our idea also incorporates modeling of interior product states. Yet, up until now, our attention has been on the integration of process data, such as that obtained from in-line sensors or sensors built into processing equipment. This could be improved by a method of data collecting that makes use of 3D-printed duplicates of food items. These copies may include sensors that enable data gathering from the point of the goods so that inferences about the processing processes and their impact on the products may be made. In order to gather intra-process data from the perspective of the products, IoT technology, particularly smart miniaturized sensors, and the utilization of 3D printing are being used. Two instances of this strategy are given. The nPotato [79] is an artificial potato placed in the field for harvesting that has sensors built into it. To determine whether the harvester is configured properly, the data is examined. During the whole travel in the supply chain, the artificial mango [70] provides improved thermal profiling. The proposed food modeling and simulation would support a very accurate view of the food items and the process when combined with data analytics of process data using machine learning (from an external process perspective) and the integration of product data from those artificial food replicas (from an internal product perspective).

VI. Results

Climate change and diseases linked to poor nutrition rank as two of the biggest problems facing contemporary societies. The content of our food is changing as a result of these issues. To reduce the health hazards and expenses connected to diabetes, obesity, and cardiovascular illnesses, less fat, sodium, or sugar must be added to foods. On the other side, concerns about animal welfare and the environmental implications of raw material manufacturing are driving a shift away from animals to plant origin protein sources. However, long-term nutritional habits can only be altered if the substitute product matches the original in terms of sensory attributes. To meet the problems of the modern world, it is crucial to comprehend how compositional changes affect the perception of fragrance.

Aromatic perception is a complicated phenomenon since it relies on physiological factors that vary greatly between individuals (saliva, respiration, etc.) and crosses over into other sensory inputs like taste and texture [80]. However, from the standpoint of food, scent release is mostly influenced by interactions between the aroma component and the food's elements (fat, arbohydrates, proteins, etc.). The partition coefficient K_{mg}, which is the ratio between the taste concentration in the diet and the amount in the air above the food, can be used to measure the strength of the these interactions.

A significant amount of information about diverse scent compounds in various food materials is available as a result of the extensive study in the topic. Consequently, it would be conceivable to create a digital twin for forecasting the K_{mg} value of fragrance compounds in foods with various compositions by

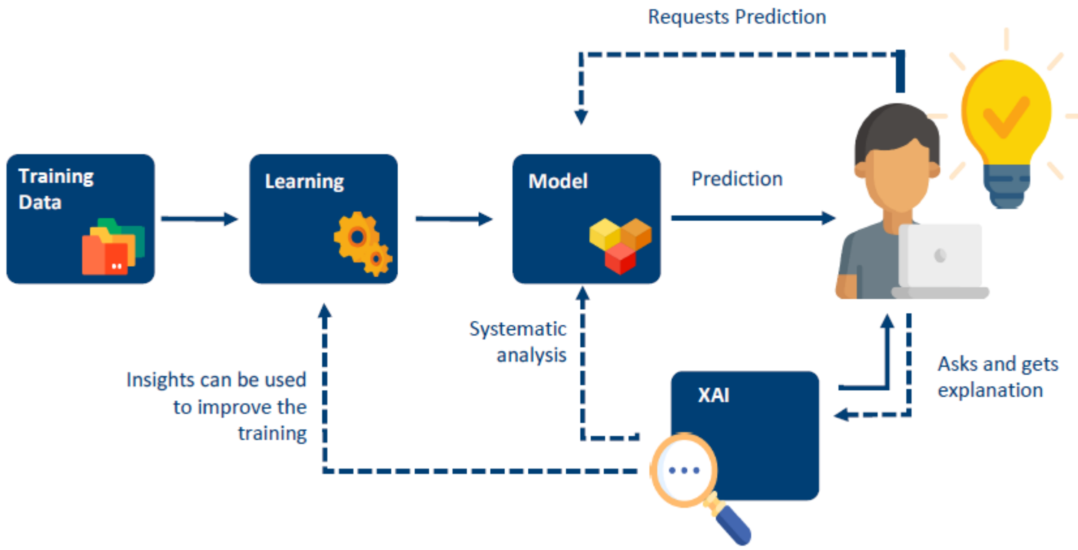

Fig. 5. Machine learning prediction with XAI explanation.

combining the models describing all known physical correlations driving scent release with machine learning. It would be possible to create the digital twin for a certain food category, such as dairy products, using the data-driven method, which combines machine learning and scientific models. Other than content, this product category exhibits significant diversity in pH and protein shape. After that, the model can be applied to items made from plants, such as soy or legumes, because the information component can modify the digital twin to fit the requirements of the other food item.

Lack of a common technique for gathering data from the real to a virtual object is one of the biggest obstacles to adopting digital twins. According to Koulouris et al., the high-quality standards, specialized equipment, and component complexity seen in the food industry and other high-value product industries are to blame for the industry's slow adoption using real-time simulation process for design and modeling [9]. Due to the variety of methodologies, the unique initiatives for creating a digital twin therefore result in greater investment costs and are therefore particularly difficult in smaller businesses and poor nations. We go over specific research hurdles for our concept of hybrid related technologies in the sections that follow.

Complex food

Application is restricted by the rigidity of the process, the complexity and variety of the raw properties of materials utilized to make food products, and the short shelf life of both the raw materials and the products made from them [9]. Additionally, as environments are constantly changing due to plants, processes, and knowledge, linked digital twins are under constant pressure to do better [81]. The assistance for modifying digital twins is particularly necessary because of the intricacy of food items.

Physicochemical model absence

Modeling and simulation technologies are hindered by poor physicochemical data [9]. Food production faces a range of foodstuffs with poorly characterized qualities, such as molecular weight, pH, water activity, and thermodynamics, which are difficult to quantify or anticipate. Additionally, biological and chemical kinetics must be understood and calculated using physics-based models [7]. Production mixtures, technical heterogeneity, and the uncertainty of the actual solution intensify this effect [82], making modeling method integration complex [7]. However, processes can estimate food processing energy, material, and yield [9].

Explaining data analysis

Data analysis uses machine learning methods. The performance-explainability tradeoff is present here. Based on physicochemical models, we plan XAI integration. Model-based XAI is relatively recent [83]. Thus, important contributions in this sector are needed for model-data analysis.

Data and Digital Twin Validation

Data validation will be crucial. The "garbage in, garbage out" concept for machine learning states that low-quality data will result in low-quality models. Validating data is crucial. Sensor failures or manual parameter adjustments can affect data quality. Data validation ensures model validity. To solve those challenges, we will include AutoML-like automatic feature engineering [84]. Additionally, digital twin model quality matters. This requires an assessment of digital twin model quality. However, context drift, where the data pattern changes and the taught models no longer capture it, might diminish quality over time. To obtain high validity for digital twin models, a metric to estimate quality and a process for lifelong learning on-the-fly are needed.

Supply-Chain Integration

Digital twins help supply chain stakeholders and activities. The multiplicity of systems and how to integrate them for digital approach is the difficulty. SAP ERP standardization can help. However, similar systems are rarer in the food industry. Due to industry needs. Thus, new ERP system kinds have arisen. A digital twin concept can mimic and optimize supply chain steps by addressing this difficulty of a holistic picture. This can boost supply chain resilience.

VII. Conclusion

In this study, we proposed integrating biophysical digital twins—data from sensors, raw material, and food science models—to capture and recreate the status of a food product and process during food processing. A hybrid digital twin can be used to reason about process adjustments and adaptations and aid product development. This study proposed using XAI processes to increase digital twin construction and expert knowledge to turn machine learning into a white-box by combining it with scientific models/simulations. The paper also shows how to use the digital twin concept in numerous case studies:

i) SeAC systems can assist adaptive food processing,
ii) product creation and food reformulation,
iii) food supply chain traceability.

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