Application of digital twin models in the fruit supply chain

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APPLICATION OF DIGITAL TWIN MODELS IN THE FRUIT SUPPLY CHAIN

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Acronyms List

AI: Artificial Intelligence

BI: Business Intelligence

CAD: Computer-aided Design

CAE: Computer-Aided Engineering

CNN: Convolutional Neural Network

CRM: Customer Management Software

CPS: Cyber-Physical Systems

CVRP: Capacitated Vehicle Routing Problem

DES: Discrete Event Simulation

ERP: Enterprise Resource Planning

GIS: Geographical Information System

IoT: Internet of Things

IT: Information Technology

MBSE: Model-Based System Engineering

MES: Manufacturing Execution System

OSM: Open Cycle Map

PLM: Product Lifecycle Management

RFID: Radio Frequency Identification

SAC: SAP Analytics Cloud

VRP: Vehicle Routing Problem

Abstract

The goal of this study is to investigate the fundamental principles underlying the use of the digital twin in common industrial operations and the agri-food supply chain, as well as the development of methodologies and frameworks for the digital twin to reduce the waste of fresh produce, particularly fruits. Thus, the study began with the identification of basic concepts related to the digital twin and its advances in the agri-food supply chain. Moreover, methodologies and a general framework for implementation have been suggested based on the operating model of the Italian food bank (Banco Alimentare Campania Onlus), which includes fruit donors, the food bank, and local charity groups as supply chain actors.

First, a detailed review has been performed to explore the fundamental concepts of the digital twin application in the main industrial activities, including production, predictive maintenance, and after-sales services. This is followed by a section with an analysis of existing literature on the use of digital twins in the agri-food supply chain, which has recently attracted the attention of many research institutes and companies. In this sector, digital twins could be used to monitor the real-time status of fresh produce as well as supply chain activities, although the approaches are not specified. In the third chapter, a machine learning-based digital twin technique was devised and applied to track the evolution of fruit quality changes throughout storage, and good prediction accuracy was achieved to develop the product twin. The fourth part of the study has focused on the creation of a cloud analytics-based digital twin capable of efficiently reducing fruit waste at the inventory level using historical time-series data. The fifth section of the study demonstrates the possible use of digital twins for near-real-time optimization of fruit deliveries from the food bank to local charity organizations, which is also regarded to have a considerable improvement in fruit waste reduction, which is mostly driven by limited fleet size and long routes during transportation. The last section presents a general framework of a fruit supply chain digital twin model, which includes an integrated solution for monitoring fruit quality status, inventory planning, and delivery optimization.

According to this research, despite a lack of common understanding of the concept, digital twin applications could enhance operational performance in many industrial sectors, including the agri-food supply chain. The proposed methods could also increase visibility in the fruit supply chain, reducing waste and meeting additional sustainability goals.

Introduction

1 Background

Digital twins are among the enabling tools of Industry 4.0 that accelerate and scale sustainability and the circular economy (Kamble *et al.*, 2022). It can integrate physical and digital objects by utilizing physical and virtual systems as well as merging data from many sources in various formats. It uses many emerging technologies including artificial intelligence (AI), the Internet of Things (IoT), big data, and robotics.

Digital twin research and applications have exploded in recent years across a variety of industries (Tao *et al.*, 2019; Rasheed, San and Kvamsdal, 2020). Many new articles and patents have been published in recent years, demonstrating this trend. Additionally, some huge companies have begun to include digital twins in their product offerings. Despite its rapid development, the concept of a digital twin is still in its infancy (Preut, Kopka and Clausen, 2021). Notwithstanding the rapid advancements in a variety of industries, their adoption in the agri-food supply chain is still in its early stages (Defraeye *et al.*, 2021). Furthermore, many critical challenges must be overcome to improve its practical implementation.

Due to the need to feed a growing population and food loss and waste, the food supply chain is among the industries facing sustainability concerns. Poor supply chain management results in the waste of a large volume of good-for-human-consumption fruit and vegetables (Mattsson, Williams and Berghel, 2018). In contrast, the global population is steadily increasing, resulting in a complicated food supply chain with an insufficient food system. As a result, there is a need for a solution to address a technological gap in the optimization of the agri-food supply chain that significantly reduces waste (Defraeye *et al.*, 2021).

In line with this, recovering food through food banks is the most effective strategy for preventing food waste in the agri-food supply chain (Garrone, Melacini and Perego, 2014; Rombach, Ricchieri and Bitsch, 2018). Food banks collect nearly expired foods, classify them by quality, and assist shops in disposing of items. Therefore, food that is still edible is transferred to food bank warehouses and supplied to the small charity organizations that distribute food to people in need. Food suppliers can also activate multiple mechanisms for redistribution that have a social impact by converting potential food waste into a useful source of food for thousands of needy people.

Food banks usually collect, store, and distribute perishable items like fruit to local charities in a traditional manner. The use of IoT applications and "digital twins" by suppliers and such organizations can alleviate various logistical difficulties linked to sorting and redistributing products before they lose their quality. To meet such demands, the agri-food supply chain requires digital twin technology as a reliable tool for tracking fresh product status, and the inventory level and optimizing the delivery process in near-real-time.

A digital twin application in the sector can have a high social impact by helping suppliers that donate food products that are losing quality. Moreover, it can provide real-time insights into the inventory level of fresh produce, which is identified as the second supply chain point, resulting in a huge waste of fresh produce in our case. In addition, improper management of the delivery process can contribute to the waste of fruit. Therefore, it is very important to have a digital twin that can optimize fresh product delivery in near-real-time. Subsequently, a general framework for improving fruit supply chains through connected digital twins should be developed.

2 Motivation

This project aims to explore the fundamental concepts of digital twin applications in typical industrial activities and the agri-food supply chain, as well as to establish a methodology and framework for their implementation. As a result, a thorough examination of the fundamental concepts of digital twin implementation and its recent advancement in the agri-food supply chain was conducted. Furthermore, the research proposed methodologies for digital twin development and implementation in the fruit supply chain while also addressing sustainability issues. The integrated solution is expected to allow fruit suppliers, distributors, and consumers to make near-real-time decisions on fruit logistics operations. The research primarily relies on SAP intelligence services and AnyLogic modeling software to propose and implement digital twin solutions in the fruit supply chain.

3 Research questions

The following issues were studied to analyze recent developments in digital twin applications and to develop a digital twin-based decision-support system in the fruit supply chain to aid in waste reduction.

1. What are the essential concepts underlying digital twin applications, and what role do they play in major industrial operations?
2. What are the most recent advancements in digital twin applications for the agri-food supply chain?

3. How could a digital twin of fruit be developed to track its quality in real-time?
4. How can we develop an automated time series-based digital twin solution for inventory planning for perishable fresh produce?
5. What is the approach for optimizing fresh fruit deliveries in near-real-time?
6. What general framework should be used to integrate digital twin solutions into the fruit supply chain?

Following the identification of research gaps, this project has primarily focused on the development of innovative digital twin methodologies and frameworks to aid the fruit supply chain in reducing waste caused by technological gaps. SAP, the Italian food bank in the Campania region (Banco Alimentare Campania Onlus), local charities, and fruit suppliers were all involved in the study.

4 Outline

Chapter 1 focused on the fundamentals of digital twins. In chapter 2, a literature survey on recent developments in digital twin applications in the agri-food supply chain is presented in detail. In Chapter 3, a method for creating a digital twin of fruit is proposed, which uses a thermal camera as a data acquisition tool to track the real-time status of the items. The proposed approach aims to help retailers and other stakeholders involved in the fruit supply chain by enhancing visibility. It also demonstrates how to create a machine learning-based digital twin using a deep convolutional neural network. Chapter 4 presents an approach for creating an automated time-series-based digital twin using SAP Analytics Cloud, which would help food banks' inventory planning process. Then, a digital twin integrated model for optimizing fruit delivery in near-real-time was proposed to tackle issues caused by uncertainties during the distribution of fruit to local charity organizations, which is also contributing to a significant amount of fruit waste. Finally, Chapter 6 presents a general framework of the fruit supply chain's digital twin-based decision-support system, aimed at reducing fruit waste and meeting other sustainability issues by integrating a fruit quality monitoring system (product twin), a time-series-based digital twin model for inventory planning, and delivery optimization, followed by the conclusion of the work.

Chapter I
Fundamentals of digital twin

I.1 Background

Nowadays, industrial management leverages cyber-physical systems (CPS) as an enabling technology for transforming experience-based knowledge into evidence-based decision-making for long-term operations, as well as using digital twin technologies to assist with product life cycle and operational management. Incorporating digitalization, data transfer, cloud computing, the use of CPS, the Internet of things (IoT), and artificial intelligence, Industry 4.0 has emerged as a fundamental strategy and trend in management (Ponomarev *et al.*, 2017).

The integration of simulation of an as-built system to mimic the life of its mirroring twin is becoming more widespread in model-based system engineering (MBSE). Most crucially, it extends the scope of MBSE beyond engineering and production to operations and service. MBSE tests and validates system characteristics early with engineers and stakeholders, for fast feedback on design decisions. The process uses modeling and simulation, which are now becoming industry norms for engineering support, decision-making, and assessing the impact of production changes by reacting quickly. As a result, this approach is increasingly being used in the design, optimization, and failure prediction.

As CPS is a set of physical devices, objects, and equipment that interact with virtual cyberspace through communication networks (Schroeder *et al.*, 2016), each physical device has its cyber part as the digital representation of the real object, called a digital twin (Figure I.1). From the beginning to the end, the digital twin holds the product's information. It has the role of monitoring and controlling the physical entity while the physical entity is sending data to update its virtual model. Thus, it enables the establishment of relations between the physical system and its virtual models for the effective execution of product design, servicing, manufacturing, and other activities during the life cycle of the product (Schleich *et al.*, 2017). The extent of reality for this purpose mainly depends on the data, model, and visualization (the quality of representation of the output). It can help companies in several stages, including the design phase, engineering phase, model reuse for operation, and service phase (Boschert and Rosen, 2016). Consequently, this will play a great role in time reduction in both development time and time-to-market, quality improvement, and the fulfillment of customer demands.

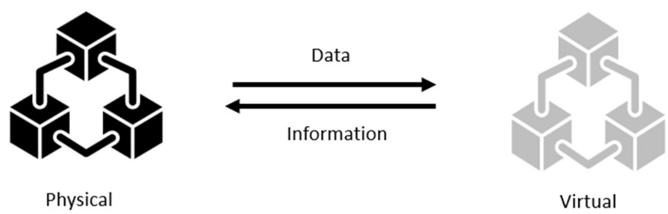

Figure I.1 *Representation of the concept of digital twin*

The motivation for this chapter comes from the need to overview the current state of the art in the application of digital twin technology both in manufacturing and service. The chapter is structured as follows: the next section focuses on the digital twins' overview, and Section 3 explains the industrial applications of digital twin models in three main domains. Section 4 discusses challenges in the implementation of digital twins. Finally, Section 5 presents the economic prospects of using a digital twin.

I.2 Digital twin overview

I.2.1 Definition of digital twin

The term "digital twin" has increasingly been mentioned in many scientific works; however, it is nebulous and, still, no unique definition has been provided. After the first definition by NASA in 2010 (Grieves, 1963), many researchers have expressed different ideas regarding the concept of the digital twin. In Table I.1, a summary of recent definitions of the digital twin is introduced.

Table I.1 *Summary of recent definitions of digital twin*

Definition	References
A comprehensive digital representation of an individual product that will play an integral role in a fully digitalized product life cycle.	(Grieves, 1963)
A digital twin is an integrated, multiphysics, multiscale, probabilistic simulation of an as-built vehicle or system that uses the best available physical models, sensor updates, fleet history, etc., to mirror the life of its corresponding flying twin.	(Glaessgen and Stargel, 2012)
A virtual representation of a physical object or system.	(SAP, no date)
Software representations of assets and processes that are used to understand, predict, and optimize performance to achieve improved business outcomes.	(Roberto Grugni, 2019)
A digital twin is a living model of the physical asset or system, which continually adapts to operational changes based on the collected online data and information and can forecast the future of the corresponding physical counterpart.	(Liu, Meyendorf and Mrad, 2019)
A virtual representation of a physical product or process is used to understand and predict the physical counterpart's performance characteristics.	(Siemens PLM, no date)
A digital twin can be regarded as a paradigm that uses selected online measurements, which are dynamically assimilated into the simulation world, with the running simulation model guiding the real world adaptively in reverse.	(Cai *et al.*, 2017)
An organized collection of physics-based methods and advanced analytics is used to model the present state of every asset in a digital power plant.	(General Electric, 2016)
A digital twin is a set of virtual information that fully describes a potential or actual physical production from the micro atomic level to the macro geometrical level.	(Zheng, Yang and Cheng, 2019)
Digital representation of a physical object.	(Frolov, 2018)
A digital representation of a real-world entity or system.	(Gartner, 2017)

An end-to-end virtual model of a physical product, process, or service to enable data-driven decision-making and to put an end to business-process inefficiencies.	(An Avent Company, no date)
A digital twin is a virtual instance of a physical system (twin) that is continually updated with the latter's performance, maintenance, and health status data throughout the physical system's life cycle.	(Madni, Madni and Lucero, 2019)
Realistic models of the current state of the process and their behavior in interaction with their environment in the real world.	(Rosen *et al.*, 2015)
The digital twin of the physical product is a digital shadow that contains all its information and knowledge of it.	(Schroeder *et al.*, 2016)
Virtual counterparts of physical devices.	(Negri, Fumagalli and Macchi, 2017)
Dynamic digital representation of a physical system.	(Madni, Madni and Lucero, 2019)
A digital twin is a dynamic and self-evolving digital/virtual model or simulation of a real-life subject or object (part, machine, process, human, etc.) representing the exact state of its physical twin at any given point of time via exchanging the real-time data as well as keeping the historical data.	(Singh *et al.*, 2021)
Linked collection of the relevant digital artifacts including engineering data, operation data, and behavior descriptions via several simulation models.	(Rosen, Boschert and Sohr, 2018)
A realistic digital representation of assets, processes, or systems in the built or natural environment.	(Centre for Digital Built Britain, 2018)
A digital twin is a dynamic, virtual representation of a physical asset, product, process, or system. It digitally models the properties, conditions, and attributes of the real-world counterpart.	(Machine, 2022)

A comprehensive physical and functional description of components, products, or systems that includes all information, which could be useful in all-the current, and subsequent-lifecycle phases.	(Boschert and Rosen, 2016)
Essentially a living model of the physical asset or system, which will continually adapt to changes in the environment or operations and deliver the best business outcome.	(Parris, 2016)
A digital twin is a life management and certification paradigm whereby simulations consist of the as-built vehicle state, as-experienced loads and environments, and other vehicle-specific histories to enable high-fidelity modeling of individual aerospace vehicles throughout their service lives.	(Hochhalter *et al.*, 2014)
A digital twin copies a physical product, process, or service through various IoT devices, pairing the virtual and real worlds	(Intellias, no date)

Apart from being a virtual representation of a physical entity, the majority of definitions of a digital twin include the bidirectional transfer or sharing of data between the physical and digital counterparts, including quantitative and qualitative data about materials, manufacturing processes, and supply chain operations. Historical data, environmental data, and most importantly, real-time data are among the data types used by digital twins (Singh *et al.*, 2021).

I.2.2 Concept of digital twin

A digital twin is a new technology that has emerged as Industry 4.0 has progressed. It creates virtual representations of physical systems during their lifetimes using real-time data from sensors, allowing system improvements and decision-making processes. It is made up of a virtual copy of a system that can run on many simulation disciplines and is distinguished by the synchronization of virtual and actual systems. Sensor data and connected smart devices, mathematical models, and real-time data are all used to power digital twin technology (Negri, Fumagalli and Macchi, 2017).

The digital twin model consists mainly of physical products in real space, virtual products in virtual space, and the connections of data and information that link the physical and virtual spaces (Figure I.1). Unlike a virtual prototype, it is a virtual replica of a physical system that is continually updated with the performance, maintenance, and health status data throughout the life cycle of the system. This is done through the real-time interaction of models and physical objects, comprising the digital definition of the product and the physical experience of the asset. Moreover, a digital twin is an evolving digital profile of the current and historical behavior of a physical product or process that supports the optimization of business performance. It uses massive, real-time, and cumulative data measurements from physical systems linked to real-world objects to offer information on the state of their counterparts, respond to changes, improve operations, and add value (Haag and Anderl, 2018; Mochida *et al.*, 2018; Saracco, 2019; Tao, Zhang and Nee, 2019a). For proper functionality, it utilizes new technologies such as the IoT, Big Data, edge computing, machine learning, and predictive analytics that can provide insights to users. Besides that, digital twins provide contextual and pertinent information on the business, its products, assets, operations, and customers; efficiency and innovation in operations; novel business models, such as increasing consumer interaction, new revenue streams, and collaboration ecosystems; and increased supply chain visibility (Aivaliotis, Georgoulias and Chryssolouris, 2019; Rasheed, San and Kvamsdal, 2020; Melesse, Di Pasquale and Riemma, 2021; Vogt, Müller, *et al.*, 2021; Wilking, Schleich and Wartzack, 2021).

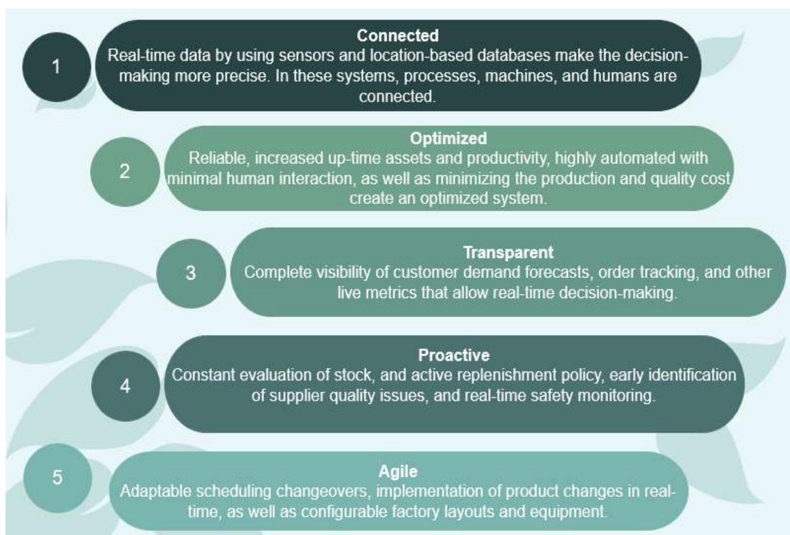

Figure I.2 *Key characteristics of smart factories*

Figure I.2 depicts the five important characteristics of smart manufacturing, according to Deloitte Analysis (Teitel, 2000; Asadollahi-Yazdi *et al.*, 2020). These attributes play a vital role in the industry 4.0 revolution, allowing decision-makers to be fully informed and keep improving manufacturing and services. As one of the enabling tools of Industry 4.0, digital twins play a vital role in improving performance in manufacturing and services. Similarly, big data analytics and cloud computing are among

Industry 4.0's nine pillars (Figure I.3), both of which involve exhaustive analysis and data collection. The IoT and cyber-physical systems use a standard communication protocol to integrate physical space and cyberspace. A virtual model of the physical world is created using simulation. The future generation of production will need to become more autonomous due to the dynamic nature of demand and the need to respond to unforeseen events. To make production more autonomous, a system called a "digital twin" is needed, which allows for seamless integration of real-time data between the virtual and physical systems.

The digital twin needs accurate data about the operations, as well as the past and present state of the system to operate properly. Thus, based on available information, the user or the autonomous system can make the right decision about actual or future events. Instead of traditional CAD or CAE models, they can figure out when to do preventive maintenance, see how the physical twin is performing, track system performance, make assumptions easier to change, let maintenance workers troubleshoot, and combine IoT data with the physical system (Madni, Madni and Lucero, 2019).

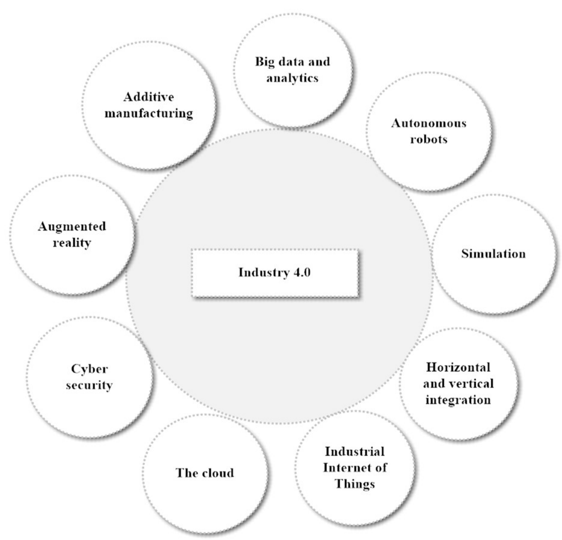

Figure I.3 *Vision of industry 4.0*

With the rise of the digital revolution, which is fueled by nine basic technological advancements, mankind has joined the fourth wave of technological advancements (Industry 4.0) (Figure I.3). Simulation is a component of Industry 4.0 and a critical tool in digital twin model for assessing the operational life of a system. For example, it can provide real-time data to reflect the physical world in a virtual model that can contain objects, machines, and humans. This enables manufacturing companies to test and improve machine settings for the upcoming product. Besides, a digital twin can assist with proactive maintenance planning and the estimation of the physical object's remaining useful life using simulation. As a result, using a predictive maintenance schedule supported by a digital twin, the user or operator can estimate the remaining life of a physical twin in operation. Nonetheless, the use of simulation models in real-time business decisions in complex and rapidly changing environments is frequently limited due to the high cost and time required for building, updating, and maintaining models (Goodall, Sharpe and West, 2019).

By reducing lead times and boosting efficiency, digital twin technology enhances operational processes, making businesses more competitive and resilient to shifting client demands. Because the physical world is tracked in real-time by a virtual world, it can assist in monitoring, optimizing, and adjusting real processes, predicting failures, and increasing process efficiency. As a result, the business decision-making process is made easier. With the advancing capabilities of IoT, predictive analytics, and cyber-physical systems, enabling technologies must overcome challenges including lack of standards, handling of large data sets, and cybersecurity (Lee, Bagheri and Jin, 2016). It's also important to build a general platform and make smart analytics better so that people can make quick decisions in a big data environment.

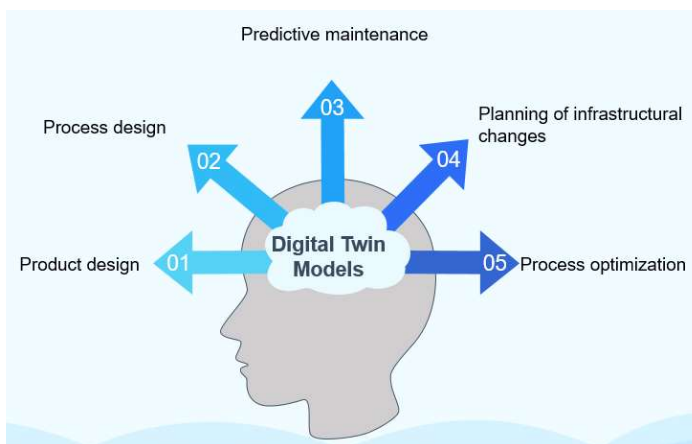

Figure I.4 *General uses of digital twin models*

Digital twin models are being applied to many areas (Figure I.4), including designing and testing products and processes, monitoring daily operations, and conducting maintenance. Product designers use digital twin models to prototype new ideas and simulate realistic models, applying what-if scenarios using product testing, system interactions, and customer experience to get real-time insights. These models can also help companies find and fix problems with production lines, improve process performance, predict maintenance, and plan changes to infrastructure, among other things.

A digital twin should provide various elements, such as the ability to expand process hierarchy, the ability to create different interfaces for different levels of hierarchy, scalability, flexibility, and the ability to view different scales of visualization, a semantical model, a framework, and a communication layer (Kostenko *et al.*, 2018b). It should also be able to handle real-time data so that diagnosis, optimization, and prediction tasks can be performed. It requires an initial digital model, knowledgebase, database, control system, and an execution environment capable of running digital models and algorithms before it can begin operation (Kostenko *et al.*, 2018a; Wanasinghe *et al.*, 2020). A data model, algorithms, and knowledge are the three fundamental components of the digital twin.

A digital twin is more comfortable manipulating and studying in a controlled environment than its physical counterpart during operations (Madni, Madni and Lucero, 2019). This flexibility is the key enabler of the cost-effective study of system behaviors and sensitivities to malfunctions and disruptions. Furthermore, data produced by different what-if scenarios can be utilized to improve designs, optimize maintenance, predict system response, validate design decisions, etc.

Digital twins frequently use machine learning to analyze multiple data streams. Simple models of digital twins, on the other hand, can be useful even without machine learning because they have a small number of variables and simple linear correlations between input and output. It uses IoT to better analyze the behavior and performance of physical twins in a practical situation (Lee, Bagheri and Jin, 2016; Schroeder *et al.*, 2016; Borangiu *et al.*, 2019).

Data acquisition, data warehousing, and data analysis are the three major pillars of digital twin development (Uhlemann *et al.*, 2017). Data collection is a critical component of digital twin deployment in production contexts. As a result, volatile data (collected through measurements and interviews) and nonvolatile data, such as employee motion, material flow, movement of production ways, production time, processing time, machine utilization capacity, real-time locating systems, and image processing systems, can be used. Data warehousing, which is a key idea for data storage employing cloud solutions and network interfaces, is another component of the digital twin. Algorithms such as artificial neural networks and optimization approaches are utilized to examine the recorded data.

The scientific community has described digital twins in a variety of ways in the literature. In some circumstances, it has become more difficult to distinguish digital twins from digital models and digital shadows (Stecken *et al.*, 2019; Tseng *et al.*, 2019; Fuller *et al.*, 2020; Bamunuarachchi *et al.*, 2021; Kalaboukas *et al.*, 2021; Vogt, Schmidt, *et al.*, 2021). To accurately define a digital model, there must be no automated data flow between the physical and digital models (Figure I.5). A digital shadow is a one-way flow between an actual and a digital object. A change in a physical object causes a change in the digital counterpart, not the other way around. If data flow between an actual physical object and a digital entity, and they are completely integrated into both ways, the model is dubbed a "digital twin."

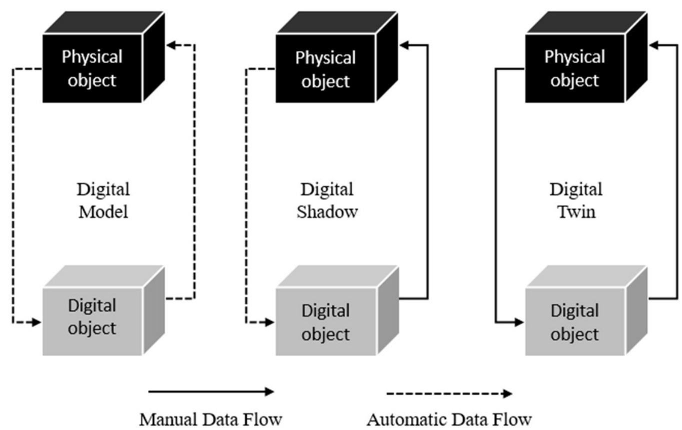

Figure I.5 *Digital model, digital shadow, and digital twin*

In a digital model, the model and actual object's parameters are similarized so that altering the parameters of the virtual object yields the same outcomes as altering the real object's parameters, and vice versa. Its validation is anticipated to include numerous manual data transfer processes, such as updates, measurements, and parameter synchronization. A good example is the design of an aircraft, which involves designing, creating a physical prototype, testing it, and then changing the digital model to achieve the intended outcome. A "digital shadow" is the automated one-way data transfer from a physical object to a digital model. By speeding up time in the simulation environment, it allowed users to gather historical data and, for example, predict the future behavior of connected items in the real world. The accuracy of the forecast is determined by the model's quality and the amount of data collected. In this case, the digital instance is unable to interact with the physical entity in real-time. The digital twin, on the other hand, enables entirely automated data transfer between digital and physical objects. According to this principle, changes in the physical object's state result in changes in the digital object, and vice versa.

I.2.3 Types of digital twin and application tools

Four types of digital twins have been identified in the literature: component twin, asset twin, system or unit twin, and process twin (Roberto Grugni, 2019). A component twin is a representation of an asset's major sub-component that has a significant impact on the system. Asset twins, on the other hand, are concerned with the entire asset. The collection of these assets will result in the formation of a network of systems, or unit twins, which will enable visibility into a range of equipment. The integration of system twins will eventually result in a more complex twin known as a process twin.

Similarly, a digital twin is divided into three categories by Gartner (2019): a discrete digital twin, a composite digital twin, and a digital twin of organizations. Individual assets, people, and other physical resources are optimized using a discrete digital twin. A composite digital twin is used in operations that require a mix of discrete digital twins and resources. An organization's digital twin is a dynamic software model that combines operational and contextual data to show how the organization operationalizes its business model, connects with its present state, responds to changes, allocates resources, and provides value to customers.

Informational digital twins, supporting digital twins, and autonomous digital twins are the three types of digital twins described by Wilking and colleagues (Wilking, Schleich and Wartzack, 2021). The concept of gathering information is described by informational digital twins. Data is gathered from the physical counterpart and processed to provide the user with useful insights. This basic version of a digital twin employs models to localize and analyze data, but it makes no recommendations for the user's next steps. This low-level digital twin ensures that data is combined in a useful way and that it is brought together. In this case, the user is responsible for furthering the application of the results. Unlike the information digital twin, the supporting digital twin processes the physical twin's data using a variety of analyses and simulations. Data is not only provided to the user in this class but it is also processed further to identify additional information and help the user in making decisions based on the processed data. The supporting digital twin typically provides this processed data directly to the user or derives direct recommendations of necessary actions based on specific models. The field of predictive maintenance is an example of such a class of digital twins. These digital twins analyze the remaining lifetime of several components based on the data they receive. The insight gained from this digital twin can be used to recommend cost-effective maintenance and repair operations. An "autonomous digital twin" is described at the third level. This type of digital twin, in addition to the supporting digital twin, uses the provided recommendations for necessary actions to influence the physical product's behavior. The goal of the autonomous digital twin is to achieve a quick response to changing physical twin data, such as variations within a production facility. The supporting digital twin can be enhanced to create an autonomous repair and maintenance system that performs these tasks automatically. However, fully independent maintenance is still in its early stages and needs a combination of algorithmic and computational techniques from AI technologies and machine learning to establish its decision-making capabilities (Khan *et al.*, 2020).

Digital twin models can be built by using different software including CAD (Grieves, 1963; Boschert and Rosen, 2016), FlexSim (Lohtander, Ahonen, *et al.*, 2018; Lohtander, Garcia, *et al.*, 2018; Mokshin, Kirpichnikov and Soiko, 2019; Tao, Zhang and Nee, 2019b; Taylor, 2019; Xu, Li and Tang, 2019) and AnyLogic (Damiani *et al.*, 2018; Barykin *et al.*, 2020), MatLab (Tsoutsanis and Meskin, 2017; Verboven *et al.*, 2020), Plant Simulation (Bambura *et al.*, 2020; Bárkányi *et al.*, 2021), etc.

To enable different modules of the digital twin, a range of supporting technologies are essential. Dynamics, structural mechanics, acoustics, thermals, electromagnetism, materials science, control theory, and other disciplines are all used in the digital twin. Physical things and processes are transferred to the virtual environment using sensors and measuring devices to make the models more accurate and closer to reality. Different modeling technologies are needed for the virtual model. Real-time monitoring of physical assets and processes involves the use of visualization technologies (Schroeder *et al.*, 2017). Moreover, simulation and retrospective technologies can help with quality defect detection and feasibility assessment. Model development technologies are required to drive model updating because virtual models must evolve in parallel with continuous changes in the physical environment.

A massive amount of data is generated during the functioning of a digital twin. As a result, advanced data analytics and fusion technologies are required to extract usable information from raw data. Data collection, transmission, storage, processing, fusion, and display are all part of the process. Application services, resource services, knowledge services, and platform services are all examples of digital twin-related services (Tao, Zhang and Nee, 2019c). Eventually, a digital twin's physical entity, virtual model, data, and services are linked to allow communication and information sharing. They include internet technologies, interface technologies, cybersecurity technologies, communication protocols, and so on. All of these technologies are needed for the digital twin to be functional.

I.2.4 Maturity framework

In the last decade, the data collection technology from physical components and the use of digital counterparts has shown a significant increase (Weyer *et al.*, 2016). The present understanding of the digital twin has grown with the development of simulation technology and the increasing possibilities of data gathering and exchange from products.

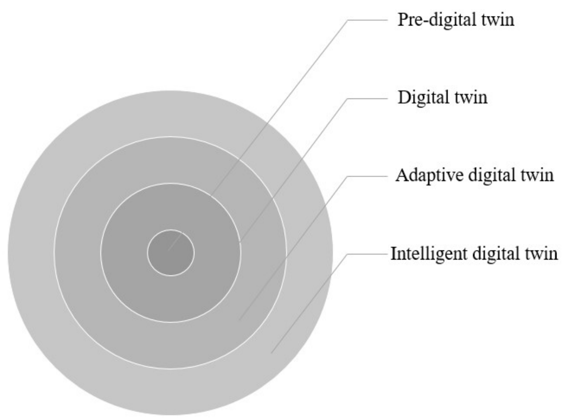

Figure I.6 *Levels of digital twin*

Makarov et al. (Makarov *et al.*, 2019) have reported different levels of digital twins (Figure I.6). The pre-digital twin is a traditional virtual prototype whose primary function is to reduce technical risks and identify issues during the early stages of design. In the early stages of the design process, a virtual prototype is typically used to verify critical individual system decisions and reduce specific technical risks. A virtual system model capable of incorporating performance, health, and maintenance data from the physical twin is known as a digital twin. While working in real-time, the physical twin can use knowledge from digital twins to improve its characteristics. At this point, the digital twin is put through a series of tests to determine how the physical twin will behave in various what-if scenarios. Any defects discovered during the digital twin inspections are used to carry out corrective actions on the physical twin. For both physical and digital twins, the adaptive digital twin provides an adaptive user interface. The ability of this digital twin to study the preferences and priorities of human operators in various contexts is its primary benefit. The adaptive digital twin has all of the features of the smart digital twin. It can also use unsupervised machine learning to figure out what objects and patterns it sees in the operational environment, and it can study the system and the state of the situation accurately even when there is a great deal of uncertainty and limited observation.

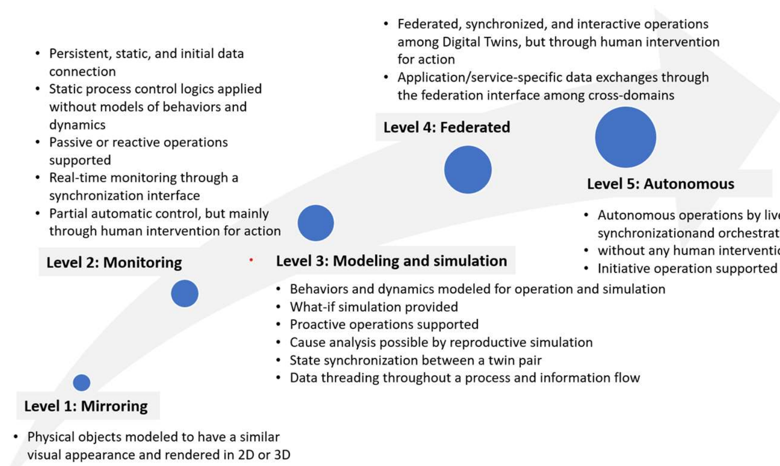

Figure I.7 *Maturity model of digital twin*

Figure I.7 depicts the maturity model of a digital twin. In this paradigm, five digital twin levels have been identified: mirroring, monitoring, modeling, simulation, federated, and autonomous (Kim, 2021).

I.3 Industrial applications

Companies are increasingly implementing digital twins, but there is no common understanding of the concepts (Table I.2). General Electric (GE), Parametric Technology Corporation (PTC), Siemens, Oracle, ANSYS, Dassault Syste`mes, System Applications and Products (SAP), and Altair have introduced platforms to build the digital twin (Bavane, Studies and Marode, 2018; Tao, Zhang and Nee, 2019a). Although these companies have their interpretations and concepts of the digital twin, they have developed their tools in common for the functionality of digital twin technology. For example, SAP has introduced the SAP Leonardo platform and SAP S/4HANA Cloud for intelligent product design to accelerate product innovation with instant collaboration, requirements-driven product development, and actionable live insights across the extended enterprise (Frolov, 2018). The company devoted its efforts to synchronizing the network of the digital twin of assets and products in real-time to accelerate innovation, optimize operating performance conditions, predict service requirements, improve diagnostics, and enhance decision-making throughout the value network.

Literature (Schleich *et al.*, 2017; Padovano *et al.*, 2018; Melesse, Di Pasquale and Riemma, 2021) has described the potential uses of digital twin models in different industrial operations. The main areas that have been identified as production, predictive maintenance, and after-sales services. It allows combining real-life data with simulation models to give good predictions using realistic data. Additionally, it gives simulation-based forecasts during normal operations, maintenance, and services.

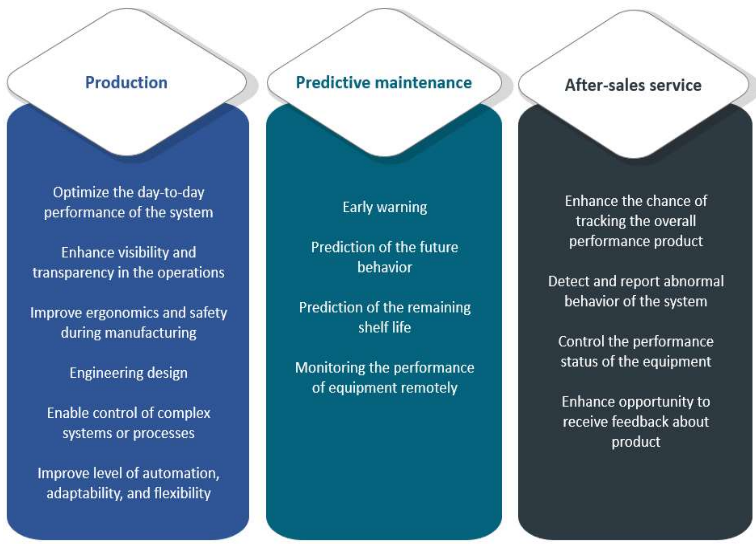

Figure I.8 *Summary of the main roles of the digital twin in three dominant application phases of industrial operations*

The concept and application of digital twins have enormous potential to create improvements and value across a wide variety of industries. The digital twin can be used to perform a variety of tasks once it has been implemented (Singh *et al.*, 2021). Some of them are in-depth analysis of the physical twin, design, and validation of new and existing products or processes, simulation of new or existing processes, simulating of the health conditions of a physical twin in a virtual environment, ramping up the safety and reliability of the physical twin, optimizing the performance of a unit, a product, a process, or a production line, tracking the physical twin's health and safety throughout its life, and predicting the physical twin's status. In addition, it can accelerate prototyping, product design, and cost-effectiveness, predict problems and system planning, optimize solutions, and improve maintenance (proactive approach), accessibility (the physical device can be controlled and monitored remotely), and reduce the risk of accidents and hazardous failure (e.g., oil and gas) (Wanasinghe *et al.*, 2020). Using digital twins to simulate and test product or system prototypes in a virtual environment reduces waste significantly (Havard *et al.*, 2019). Another advantage of the digital twin is its ability to synchronize data scattered across different software applications, databases, and hard copies, which simplifies the process of accessing and maintaining data in one location. Furthermore, digital twins can be used to create more efficient and clear safety training programs than traditional ones. The following section will go over digital twin implementations in general, categorizing them as production, predictive maintenance, and after-sales services (Figure I.8).

I.3.1 Predictive maintenance

These days, industries are shifting from reactive to predictive and proactive maintenance to improve efficiency, extend the life cycle, and reduce the operational costs of their asset. The capability of the digital twin to predict the future behavior of an operating system or assets is considered a great input in large industrial sectors. By using real-time data and data-driven analytics, a digital twin can predict future behavior and the impact of the current operating condition on the remaining life of an asset (Liu, Meyendorf and Mrad, 2018; Altun and Tavli, 2019; Barthelmey *et al.*, 2019; Rajesh *et al.*, 2019; Werner, Zimmermann and Lentes, 2019). Therefore, identifying potential problems can enable asset owners to perform predictive maintenance to reduce downtime and operational cost. Thus, a digital twin can deliver accurate forecasting of system failure using incoming data from physical assets (Liu, Meyendorf and Mrad, 2018; Cavalcante *et al.*, 2019; Matino *et al.*, 2019; Abdrakhmanova *et al.*, 2020; Rasheed, San and Kvamsdal, 2020) providing optimization, early warning, and prediction capabilities. This functionality of the digital twin is expected to have a paramount role in the performance of future industries. For example, the use of digital twins in the predictive maintenance of aircraft has been described by (Liu, Meyendorf and Mrad, 2018). The study has applied the use of integrating the simulation and modeling ecosystem to maintain, overhaul, and repair aircraft using IoT and cloud computing systems. The data fusion technique was applied to improve the velocity, variety, and volume of data flow. Similarly, research by (Ganguli and Adhikari, 2020) has created a mathematical framework to establish a digital twin for aircraft dynamic systems using sensors, the IoT, and cloud computing systems.

I.3.2 Aftersales services

According to the study (Dombrowski and Malorny, 2017), after-sales services can improve profit by 80% in many companies, providing competitive advantages. Despite this, the research effort on the use of digital twins in this application phase is still limited.

A digital twin can support companies by monitoring their sold items for sudden failure. Therefore, the capability of monitoring the overall performance and maintenance history of products can help manufacturers gain more trust from their customers by detecting abnormal conditions and providing insights for maintenance. Besides, a digital twin can enable the service sector to achieve the goal of smart manufacturing (Magistrale, Marco and Peruccio, 2019; He and Bai, 2020; Ruzsa, 2020) improving information visibility throughout the life cycle. For instance, studies (Heber and Groll, 2017; Hasan *et al.*, 2020) have shown the application of digital twins to trace the status of devices. The effectiveness of this traceability and security can be improved with the use of blockchain technology. Adaptation of this technology is considered a key solution to monitor physical objects from production to after-sales. With the help of the digital twin, companies can also improve interaction with their customers, provide support, and receive feedback about their services. Ultimately, they can improve brand loyalty by adapting to the needs of customers. The study has shown how manufacturers were able to optimize the operation of smart farming for potato harvesting using feedback from customers (Kampker *et al.*, 2019).

I.3.3 Production

A digital twin is a virtual model characterized by a continuous update of the actual state using real-time data. This can be helpful to evaluate an operating system under different conditions. Therefore, using what-if analysis, various scenarios of the production system can be improved and optimized. Moreover, visibility and transparency of operations can be enhanced through virtualization during production, and the behavior of individual devices can be monitored to integrate the whole system of manufacturing for a better business outcome. The digital twin also has an important role in the development of new value creation using product-as-a-service business models. For instance, a study (Qiao *et al.*, 2019) described the use of this approach in the shop-floor management system in the Logistics Learning Factory.

Small and medium-sized enterprises can improve the capability of real-time data acquisition systems and operational performance using digital twins

(Uhlemann *et al.*, 2017; Kunath and Winkler, 2018). A digital twin can enhance the virtual representation and synchronization of the production system in the operational environment. For example, research (Tammaro *et al.*, 2017) has described the application of digital twin in object tracking using industrial robots. In this case, detected objects have been added to the digital twin model of the cell along with the robot, creating a synchronized virtual representation of the system.

Studies (Malik and Bilberg, 2018; Sun *et al.*, 2020) have shown the use of digital twins in the simulation of the work environment for assembly tasks supporting the cooperation between humans and machines. It has also demonstrated the importance of the digital twin in the human-robot production system in the life cycle ranging from design to operation, proposing an implementation framework and using a case study to demonstrate the advantages. Accordingly, the advantages have been described in terms of risks of financial loss and due to human injury in a real-world environment.

A digital twin can improve the ergonomics and safety of the manufacturing system. The study (Arisoy *et al.*, 2016) has demonstrated the application of digital twins in the production system to optimize the safety and ergonomics of the working environment. Similarly, it has the advantage of improving the level of automation, adaptability, and flexibility (Tolio *et al.*, 2017; Lohtander, Garcia, *et al.*, 2018; Barthelmey *et al.*, 2019), operational efficiency (Barthelmey *et al.*, 2019), cost reduction (Bevilacqua *et al.*, 2020), solving problems of regulatory difficulties (Hu, Shi and Jiang, 2020), and the creation of new revenues by adding product features and business models (Etienne, 2018). Production optimization is another key function of the digital twin on which many researchers are currently focusing (Werner, Zimmermann and Lentes, 2019). The use case in petroleum industries (Min *et al.*, 2019) describes the effectiveness of digital twin technology to optimize production by using machine learning-based frameworks. Moreover, the digital twin improves the status of companies in digital monitoring and enhances the function of interconnected devices throughout the production system (Vathoopan *et al.*, 2018; Fera *et al.*, 2020). It can be used as a support tool for other industrial operations, such as order management (Vathoopan et al., 2018) and horizontal and vertical integration of production systems (Vathoopan *et al.*, 2018), and horizontal and vertical integration of production systems (Vathoopan *et al.*, 2018). These enable companies to meet customer needs and manage their resources properly. Besides, the digital twin improves the safety and reliability of operations through condition monitoring of the production system (Moi, Cibicik and Rølvåg, 2020).

Deploying digital twin technology can enable companies to optimize factory operations while enhancing equipment usage and product quality using data analytics. Therefore, through a clear view of raw material and parts flow, managers can schedule operations and deliveries of their products with improved efficiencies. Furthermore, it will enable manufacturers to anticipate product demand, maintenance needs, and design improvements.

I.4 Challenges in the implementation of digital twin

Implementation of the digital twin is still facing challenges, including a lack of detailed methodology and standards, difficulties in collecting and storing large data (Schleich *et al.*, 2017; Wanasinghe *et al.*, 2020), developing a data acquisition system, synchronization problems, modeling of a complex system, lack of awareness, resistance companies to adopting the technology (Lohtander, Garcia, *et al.*, 2018), and difficulties in constructing, understanding, controlling and simulating real-time changes in the system. Moreover, combining multidisciplinary knowledge and providing enough data are the two most difficult aspects of implementing digital twins (Henrichs *et al.*, 2022).

High-fidelity models are required to simulate and test the product or process in a virtual environment, by reducing development time and cost (West and Blackburn, 2017). The issue of high investment costs and data security is still a question for many companies looking to make digital twin part of their daily lives. There are also problems related to the lack of suitable business models, and the use of digital services and goods is still new and implementation is tough for many manufacturers (Lohtander, Garcia, *et al.*, 2018).

A study (Singh *et al.*, 2018) has identified engineering, technology, commercial, data, and others as challenges. Engineering challenges are raised by the complexity of the system to make system predictions and the lack of standards to ensure efficient communication, human and product safety, the security of the data, and structural integrity. Technological development is also a factor that is hindering the implementation of digital twin technology. This can be evaluated in terms of cost and time. As a result, the highest cost of IT facilities and the long-term need to develop appropriate technologies. These issues can be addressed by removing cultural barriers, changing attitudes toward data sharing, and investing in better software and services. The commercial challenge includes scalability issues (Altun and Tavli, 2019) due to the architecture, the capability to change the level of parameters, the complexity of the supply chain, and computational power. Information sharing is considered the biggest obstacle raised by the complex policies of companies regarding the ownership of data.

The technological challenge is related to the servitization issue because service delivery is still difficult and dependent on the company's business model, customer management, and risk management. Therefore, end-to-end integration should be developed throughout communication to solve the issue of privacy risk and improve transparency in data flow during the use of digital twins.

Another barrier to using digital twins is cybersecurity, which consists of several pillars such as security, data encryption, security audit, monitoring live events and responding to incidents, identity, and device management (Wanasinghe *et al.*, 2020). A digital twin is an attractive and vulnerable security risk. To ensure data security, digital twins should be supported by a security audit for the visibility of the transaction and to identify the devices and users. Moreover, it is mandatory to ensure the right level of access to the activities they have performed. Similarly, data encryption can be used as a solution to protect against the injection of false data by malicious actors, and it should be enabled by the capability of live event monitoring and responses to detect abnormal behavior during the operations. Thus, digital twin developers should be able to authenticate and know the identity of users to monitor who is attempting to access and send data to the dataset or system.

I.5 Economic prospects

In most cases, a product experiences multiple processes before creating a working prototype, which is very expensive due to the significant contribution of time and labor. A digital twin can enable the reduction of defects during actual production by allowing tests and simulations in the virtual environment. Therefore, it is much cheaper to correct mistakes through digital representation than in the real-world. Hence, the application of digital twins can reduce costs during production and maintenance.

Effective information management will lead to better business and societal outcomes by improving decisions, financial savings, performance, and service. Over 50 billion machines could be connected between 2020 and 2030, with around seven billion internet users (Parris, 2016). This will be a great opportunity for digital twin technology to advance. The digital twin market is expected to grow at a compound annual growth rate of 37.87 percent by 2023, reaching 15.66 billion dollars.

The benefits of integrating the digital twin model into a real-world system are numerous. It enables a company to take immediate action in the event of a problem and optimize the asset's performance. Companies will be able to optimize the process, understand and predict machine performance, and the business as a result of this. In the end, this will result in a significant reduction in maintenance costs, as well as a reduction in the risk of breakdowns, downtime, and material losses, as well as increased efficiency and quality (Ponomarev *et al.*, 2017; Goodall, Sharpe and West, 2019). As a result, the values of the digital twin translate directly into measurable business outcomes such as reduced asset downtime and maintenance costs, improved plant efficiency, shorter cycle times, and increased market agility. Similarly, by reducing rework, the development of a full-life-cycle digital twin can improve the manufacturing process. Furthermore, incorporating digital twins into manufacturing systems can improve production quality, lower costs, and raise competitiveness.

Furthermore, digital simulations will shorten the time between product development and use in manufacturing, as well as the realization of firms' market-enhancing innovation capabilities (Goodall, Sharpe and West, 2019). Digitalization will also overcome the scarcity of resources and goods by allowing consumers and the production environment to interact. In general, the digital twin offers numerous benefits that increase the likelihood of entering new markets and services. As a result, the efficiency of business delivery will be improved throughout the value chain.

Chapter II
Advances of digital twin applications in the agri-food supply chain

II.1 Introduction

Many challenges confront the food industry, including the need to feed a growing population, food loss and waste, and inefficient production systems (Henrichs *et al.*, 2022). A large amount of food in good condition for human consumption is wasted globally as a result of poor management along the supply chain. In contrast, the global population is steadily increasing, resulting in a complex food supply chain with poor food management systems. According to the report (Lipinski and Robertson, 2017), an estimated 30% of food is wasted globally somewhere along the food supply chain, while the world's total population is expected to be 9.1 billion by 2050, possibly requiring a 70% increase in food availability. The United Nations' Sustainable Development Goals 12.3 program aims to cut per capita food waste at retail and consumer, as well as at a production and supply chain level, in half by 2030. Concerns about food security, sustainability, productivity, and profitability have grown in importance as the world's population has grown. Environmental and climate change issues are also becoming more economically pressing. As a result, smart technologies and techniques that work well together have been widely considered recently.

Food waste occurs at every stage of the supply chain. It can, however, be turned into a resource by supporting people in need through food redistribution channels. Many technologies have been implemented in recent decades to reduce the quality loss of fresh produce from farm to fork. Despite this, nearly half of the loss occurs at various stages of the supply chain, such as pre-cooling, packaging, transportation, and storage (Onwude *et al.*, 2020). Extracting the maximum value from these resources and encouraging the reuse of wasted foods are both essential for a more sustainable future.

Food waste has a huge impact on issues like food security, economic development, and pollution in the environment. Food insecurity is a worldwide problem that leads to many deaths and health problems. Unfortunately, world hunger is on the rise as a result of issues primarily related to poor management, which can result in a large volume of food being lost. This problem is particularly prevalent in fresh foods, which, due to their biological composition, cannot maintain their quality for an extended period. The inefficiencies of the entire supply chain play a big role in perishable food losses (Jedermann *et al.*, 2014). They should also be delivered quickly to maintain their freshness.

To address these issues, possible solutions can be implemented throughout the food supply chain. The use of the digital twin has recently piqued the interest of the food and agricultural industries. Its implementation is a critical step in real-time (or near-real-time) system monitoring and product quality evolution during the pre-harvest and post-harvest stages of handling. This type of technology allows stakeholders to reduce the waste of fresh produce such as fruits and improve stock visibility. It also makes the decision-making process easier. For example, users can apply discounts to quickly deteriorating foods in stock, start the donation process to charity organizations, or even discard them. This will have a significant social impact on the business sectors, in addition to waste minimization.

Despite recent concerns about monitoring the real-time status of food products, the agro-food industry continues to struggle with ensuring supply chain traceability due to a lack of effective data acquisition systems. As a result, food products, particularly fruits, lose their quality if their status in specific supply chain locations is not properly investigated. To ensure food safety and monitor the shelf life of perishable products, integrated food management is required throughout the supply chain. Due to their short shelf life, these items require special attention and often result in complex logistical management processes. Fresh food deterioration is linked to a variety of factors, including their chemical, physical, or biological origin (La Scalia *et al.*, 2017).

Digital twins, which combine real-time and real-world data to build a digital copy of physical entities, appear to be a potential tool. By definition, digital twins are representations of living and non-living entities and processes that can be used to analyze and simulate interventions on these entities and processes (van der Burg et al., 2021). It is primarily used in manufacturing, predictive maintenance, and after-sales services (Melesse, Di Pasquale and Riemma, 2021). However, recent research findings indicate that the research community is highly motivated to implement digital twins in the agri-food sector. It is a collection of computational models that serve as a virtual representation of the product, process, or operation in question (van der Burg *et al.*, 2021). Implementing the digital twin will result in several benefits, including increased product quality and shelf life, more efficient resource utilization, improved maintenance, optimized production planning, reduced losses, improved logistics, energy savings, and increased overall visibility. Despite these opportunities, the use of digital twins in the agro-food sector has received little attention. The chapter will discuss recent approaches to digital twin applications in the agro-food supply chain. Section 2 describes the methodology of the review. Section 3 summarizes the findings of the bibliographic analysis conducted in the designated area. Section 4 provides an overview of the discussions extracted from the literature.

II.2 Method

The scope of this work includes an overview of concepts, definitions, and current trends related to the application of the digital twin in the agri-food supply chain based on the outline described in Figure II.1. This review has used the Scopus database as a data source with keywords ("digital twin") AND ("post-harvest" OR "food"). The review used 43 papers published in the years between 2018 and 2021.

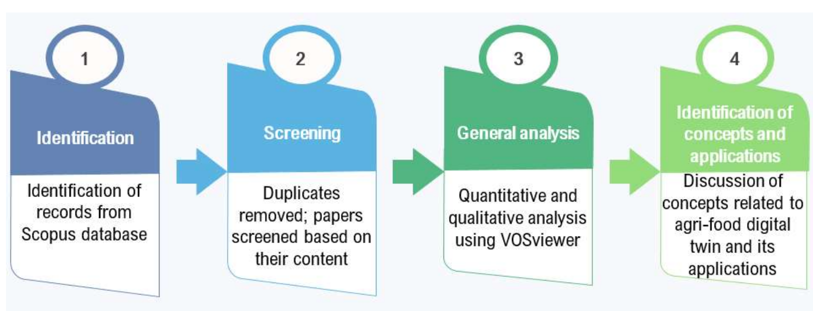

Figure II.1 *Review process*

The primary inclusion criteria were designed to grasp how digital twins create value in agri-food supply chain management. Thus, the review process was guided by the following criteria during the screening process: conceptual and modeling studies on the implementation of digital twins at different agri-food supply chain levels. The papers were retrieved on July 25, 2021, and the references were saved in plain text format with the information of the titles, keywords, author information, abstracts, and references. This data was considered for descriptive analysis and further investigation. VOSviewer software was used to perform an analysis of co-authorship, citation, co-citation, and co-occurrence analysis for countries, institutions, authors, and keywords (Ritchie, Teufel and Robertson, 2008; Wu *et al.*, 2021). Co-authorship analysis measures have been applied to analyze the similar relationships among works. In this regard, using many co-authored items and citation analysis shows the number of papers they cited each other. Similarly, co-citation and co-occurrence analysis shows the relationship between items based on the number of times they are mentioned together and the number of works in which they appear together. In addition, total link strength attributes have been used as standard weight attributes to indicate the total strength of the links between an item and other items. The total link strength attribute indicates the total strength of the co-authorship links of a given researcher with other researchers.

II.3 Results

II.3.1 Trend of Global Publications and classification of papers

Scopus yielded a total of 43 published works from the year 2018 to July 25, 2021, during the search. The global trend of digital twin research in food and post-harvest management has steadily increased, as shown in Figure II.2. This is important evidence of the growing interest in implementing digital twins in the sector.

Figure II.2 *Records of publications*

In the search, no published work was obtained before the year 2018. This indicates that digital twin adoption in the agri-food sector is still in its early stages. The global trend of publication has been steadily increasing in the past 4 years, with incomplete data for the year 2021.

Most contributions (39.5%) are through scholarly articles in reputed journals, followed by conference papers (34.9%), reviews (14%), conference reviews (9.3%), and book chapters (2.3%). Therefore, most of the contributions come from articles, followed by conference papers, reviews, and book chapters (Figure II.3).

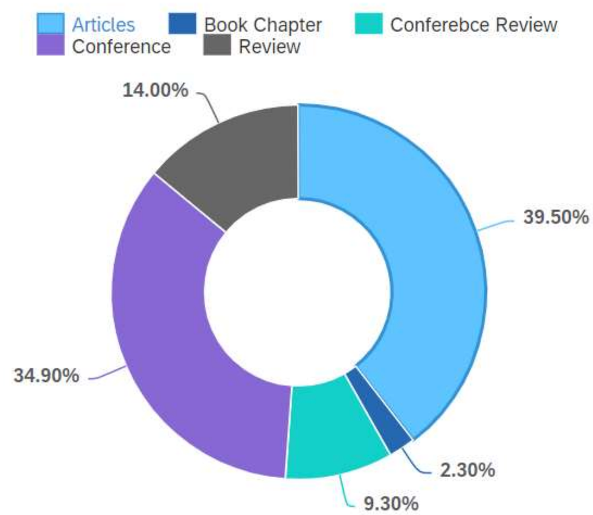

Figure II.3 *Documents by type*

II.3.2 Contributions of institutions

A total of 93 institutions contributed to the publications on digital twin applications in the agri-food sectors. The Empa-Swiss Federal Laboratories for Materials Science and Technology was the largest contributor in terms of the number of publications, with 5 papers, followed by Wageningen University & Research and the Russian Academy of Sciences, and KU Leuven with 4 and 3 papers, respectively. The top 10 most influential institutions and the number of articles in each institution are presented in Figure II.4.

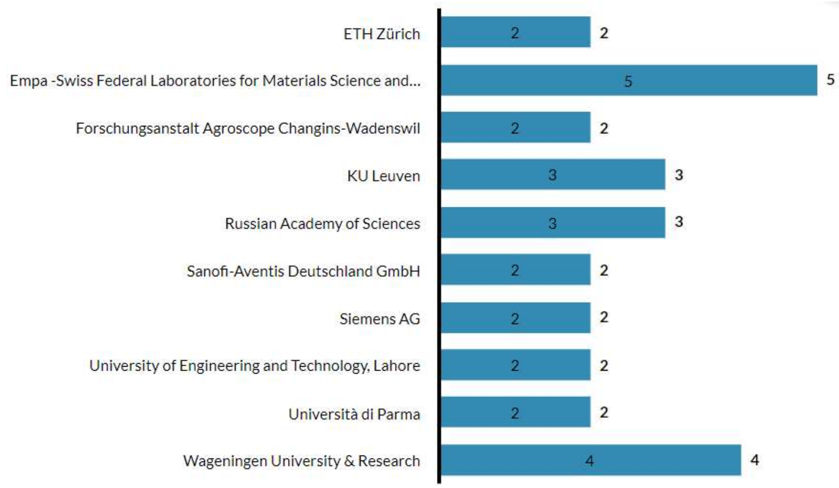

Figure II.4 *Documents by affiliation*

II.3.3 Contribution of authors

The top authors who published their work in the field are presented in Figure II.5. From Scopus, 133 researchers have participated in 43 publications. A total of 23 papers accounted for 53% of the total search results. The top 10 authors contributed a total of 23 papers.

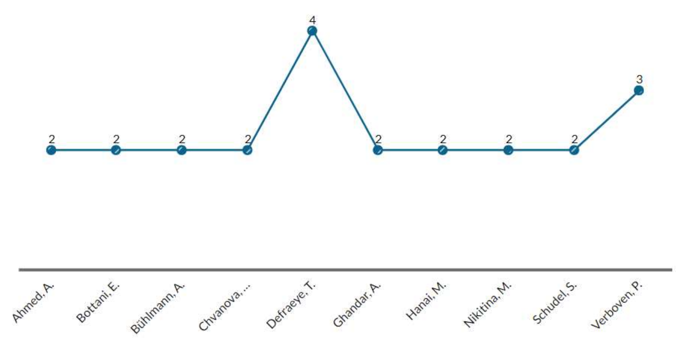

Figure II.5 *Contribution of authors*

Defraeye, T. from Switzerland, was the author with the highest number of publications, followed by Verboven, P. from Belgium, and the rest of the authors in the top list have the same number of publications, contributing 2 papers each.

II.3.4 Citation analysis

Many methods have been used to assess a publication's relevance. Citation analysis is the most widely used method for determining a publication's popularity by assessing how often it is mentioned by other publications (Bhandal *et al.*, 2022). Citation analysis produces an inter-subjectively verified conclusion independent of the experts' subjective thoughts and judgments. Moreover, the method provides a "live" view of ongoing research. In our case, the citation scores of the authors are illustrated in Figure II.6. In the figure, the size of circles (nodes) indicates the absolute number of documents cited, and the lines represent the connectivity between documents.

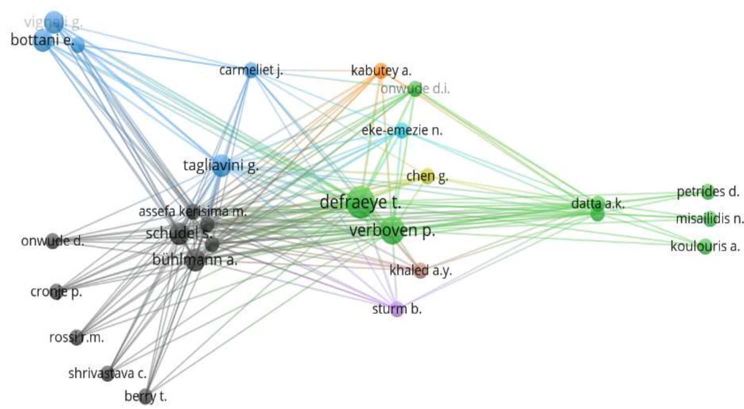

Figure II.6 *Citation by authors*

As for country co-authorship analysis, the United States was at the center of research on the application of digital twin in the food and post-harvest areas with a total link strength of 19, followed by Germany and Switzerland, with equal contributions in the field of research illustrated in Table II.1. In this analysis, publications originating from 24 countries were examined, and for each of the countries, the total strength of the co-authorship link with the other country was calculated.

Table II.1 Distribution and international cooperation of countries that are involved in research

Country	Documents	Citations	Total link strength
United States	12	62	19
Germany	5	6	12

Switzerland	6	40	12
Australia	5	107	8
Belgium	4	29	8
France	3	105	7
Czech Republic	1	3	5
Nigeria	1	3	5
Austria	1	2	3
Ethiopia	1	15	3

The total link strength has shown a strong correlation with the number of documents each country has contributed. However, country-wise citation doesn't show a clear relationship with the strength of the total link as shown in Figure II.7. Using VOSviwer, the top four nations with the highest citation scores were identified as the Netherlands, Austria, France, and the United States, followed by Switzerland, Belgium, and others.

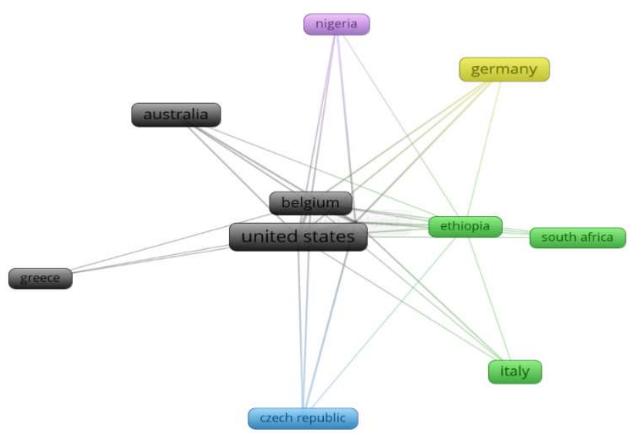

Figure II.7 *Citation relation by countries*

II.3.5 Bibliographic coupling of sources

Over alternative network structures, such as co-authoring and co-citation, bibliographic coupling was chosen for analysis. Figure II.8 shows the bibliographic coupling of the journals with network visualization based on weighted documents with a minimum threshold of 1 publication per source. Of the 28 sources, IEEE Access, Communications in Computer and Information Science, Food and Bioproducts Processing, ACM International

Conference Proceeding Series, and Advances in Biochemical Engineering Biotechnology are among the top 5 sources of publications in the contribution.

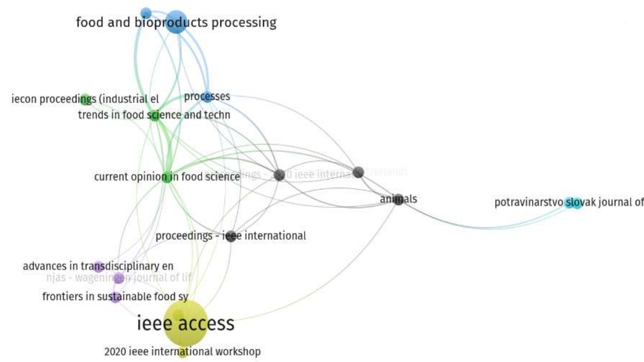

Figure II.8 *Bibliographic coupling of the sources based on document weight*

In the Scopus search, 38 journals have been identified as data sources for the publications. For each of the sources, the total strength of the citation links with other sources was calculated, and the top 10 journals in the total link are presented in Table II.2. IEEE Access has the greatest number of publications (4) and 21 citations with a total link strength of 12. The NJAS-Wageningen Journal of Life Sciences received the most citations (103) and is the primary scientific platform for research on agricultural production, food and nutrition security, and natural resource management. On the other hand, the Journal of Trends in Food Science and Technology is found to be the best journal in terms of total link strength (45).

Table II.2 *Top 10 sources and total link strength*

Sources	Documents	Citations	Total link strength
Trends in Food Science and Technology	1	1	45
Current Opinion in Food Science	1	13	36
Processes	1	3	30
Resources Conservation and Recycling	1	15	22
Food and Bioproducts Processing	2	6	17

Proceedings IEEE International Symposium on Circuits and Systems	1	2	14
Animals	1	0	13
IEEE Access	4	21	12
NJAS - Wageningen Journal of Life Sciences	1	103	10
Communications in Computer and Information Science	1	3	8

II.3.6 Keyword analysis

Keyword co-occurrence analysis is an important approach to tracing current developments in the research topic. This analysis was used to define the area of study focus for each cluster. Keywords can accurately describe the contents of a document and it's predicated on the premise that a collection of keywords can represent underpinnings and that their co-occurrences can disclose their relationship with those themes. This is an approach to determining scientific developments by creating high-frequency keywords using the VOS viewer. The density map in Figure II.9 was created using VOSviewer and the result shows that there were 534 keywords in the 43 papers. Some of the keywords that appeared in the literature include digital twin, internet of things, artificial intelligence, machine learning, supply chains, computer models, simulation, fruit, thermal processing (foods), agriculture, food products, etc.

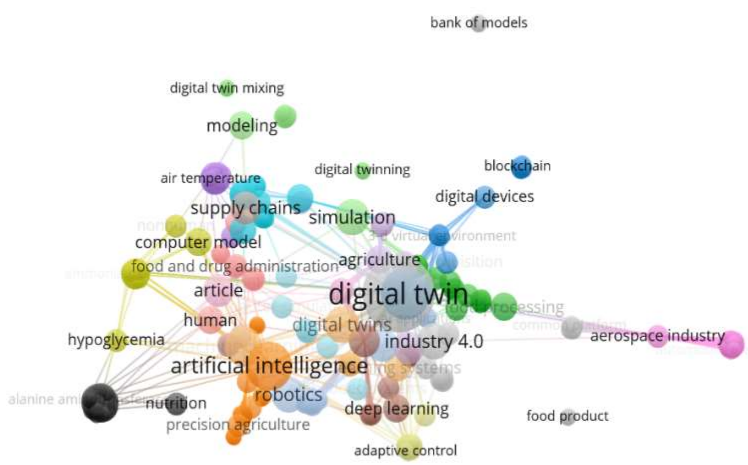

Figure II.9 *Co-occurrence network map of keywords*

Different clusters have been shown in the figure, and the keyword "digital twin" is still dominant. This keyword appears 22 times and has a total link strength of 415, indicating a strong relationship with the other emerging topics. It is also shown that the co-occurrence of keywords related to food and post-harvest is limited based on the analysis, which implies the application and understanding level of the digital twin concept in the area is low but promising for the field in the future.

II.3.7 Contribution of funding agencies and organizations

Recently, research into the application of digital twins has attracted many companies. The top 10 funding agencies that have sponsored the output of research in food and the post-harvest sector are shown in Figure II.10. In the ranking, Fonds Wetenschappelijk Onderzoek is the first funding agency based in Belgium, followed by the European Commission, Italian, Belgian, and Australian funding agencies.

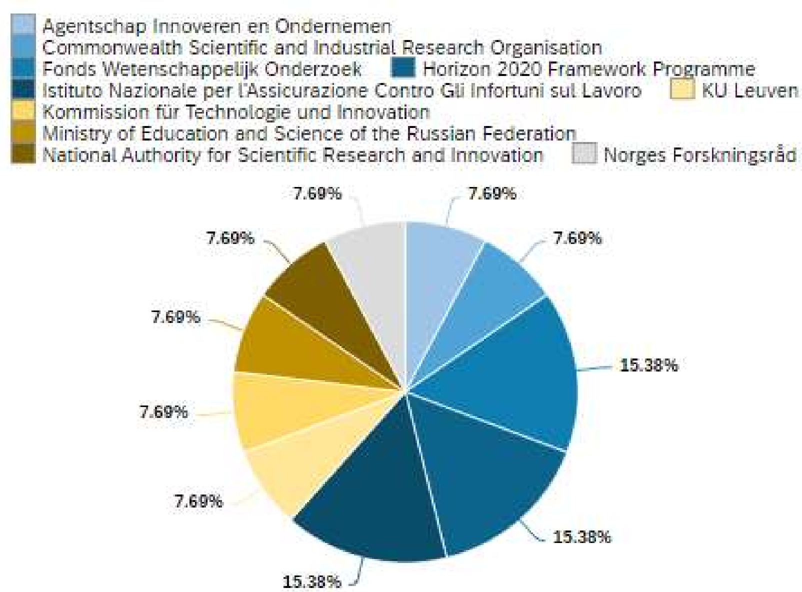

Figure II.10 *Documents by funding sponsor*

The lists in the figure are based on the Scopus database. For each of the 93 organizations, the total strength of bibliographic coupling is presented in Figure II.11. The result in VOSviewer shows that Empa, Swiss Federal Laboratories for Materials Science and Technology, has contributed the highest research outputs with 36 citations and a total link strength of 2883, followed by MeBioS–postharvest group, a Belgium-based organization, contributing a citation score of 16 and a total link strength of 1133. Then, Aalto University School of Electrical Engineering (Finland), Adaptation Physiology Group (Netherlands), and Addis Ababa Institute of Technology (Ethiopia) took the 3rd, 4th, and 5th places, respectively.

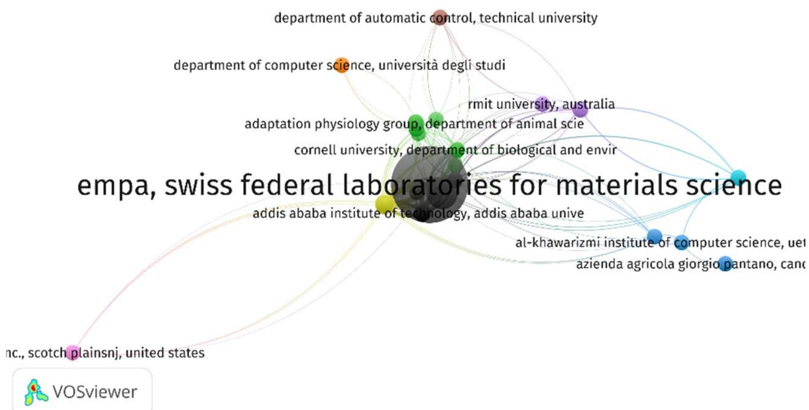

Figure II.11 *Institutes involved in the research*

II.4 Discussion

In this review, the patterns of research were examined, identifying the main publications, contributing countries, authors, citations, and funds, and measuring the contribution of different institutions. The finding showed that the research on the application of digital twins in the food and post-harvest areas is in its infancy over the study period of 2018 to July 25, 2021. Only 43 published works were found in the Scopus database, cited 234 times. In terms of publication contributions, the United States is becoming the dominant contributor, followed by Switzerland, the Netherlands, Belgium, and South Africa. However, the highest citation scores come from Australia, France, and the United States, in decreasing order. According to the indications of the current progress in research activity, the Netherlands is putting a lot of effort into digital twins related to life science. Wageningen University, in particular, is one of the most enthusiastic supporters of Industry 4.0 (Catal and Tekinerdogan, 2019) and has a strong reputation in agriculture, forestry, and artificial intelligence.

Moreover, projects like the European IoF2020 project have shown promising results in the application of digital twins in the agriculture and food domains. Overall, it can be predicted that more outputs may be available in the coming years. In the documents, more emphasis has been given to the concept and application of digital twins at the product level and across the whole food supply chain. Therefore, the following section will focus on the three focus areas, including the concept of a digital twin, digital twin-based monitoring for agro-food products, and its application in the entire food supply chain.

II.4.1 Concept of the digital twin in the agri-food domain

Digital twins and other emerging technologies like the IoT, Deep Learning, Data Science, Edge Computing, and Augmented Reality are bringing new opportunities and solutions for many problems related to agriculture, plant sciences, and food sciences (Catal and Tekinerdogan, 2019). A digital twin is a digital representation of merely anything: it can be an object, product, or asset (Marmolejo-Saucedo, Hurtado-Hernandez, *et al.*, 2020). With the most agreed definition, it is a virtual representation of a physical asset (Onwude *et al.*, 2020; Defraeye *et al.*, 2021; Neethirajan and Kemp, 2021; Scheper *et al.*, 2021). In food and post-harvest, it realistically represents a physical object or asset, mirroring its behavior. "A digital twin is a digital representation of a physical object with underlying models that can simulate the real-life behavior of, in this case, fresh produce" (Maersk, 2021).

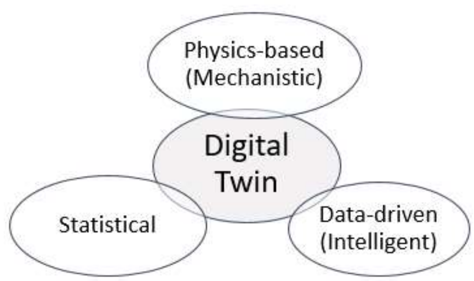

Figure II.12 *Digital twin types in the agri-food supply chain*

As illustrated in Figure II.12, the digital twin's underlying master model in the food supply chain can be a statistical, data-driven, or physics-based model (Defraeye *et al.*, 2021). An analytical model that uses recorded air or fruit pulp temperature at a given site to determine food quality loss using a kinetic rate law, which was calibrated empirically with experimental data by a statistical model, is a typical example of postharvest technology. Artificial intelligence techniques, such as machine learning, are utilized for model building, calibration, verification, and validation in the case of a data-driven model. Machine learning models can be trained in a variety of ways, including supervised and unsupervised learning. The training data could include things like horticultural-produce storage settings and the fresh horticulture produce's measured biological response over time. A back-propagation neural network is used in one application to forecast the impacts of the microclimate on the evolution of fruit quality in the cold chain of fresh horticulture output. Another application is the use of data-driven models to improve transportation logistics and maintenance while reducing quality loss. People who understand deep learning techniques and add data to them on their own may be able to tackle some of these challenges. Multiphysics modeling and simulation are used in physics-based approaches to model and simulate the relevant physical, biochemical, microbiological, and physiological processes, including the CAD geometry of the fruit, material property data, and the physical model's beginning and boundary conditions. This is accomplished by employing a mathematical definition of the relevant biological processes, such as biochemical processes, that affect fruit quality parameters.

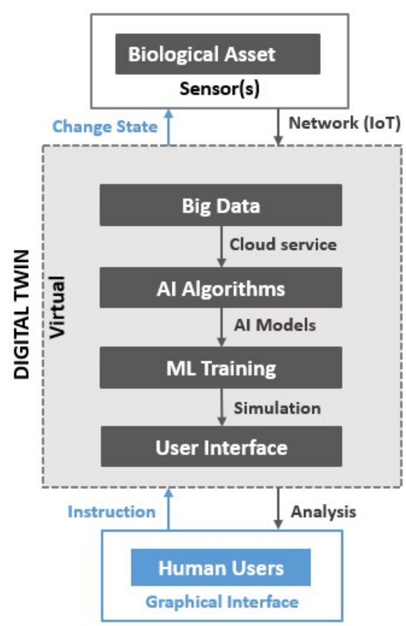

Figure II.13 *Concept of a digital twin for biological assets*

The digital twin obtains real-time feedback on how a biological object is interacting with its surrounding environment (Figure 13). For this purpose, sensors are used to receive data through internet networks in a secure way. A large volume of data can be received during this process; therefore, cloud servers are needed to manage big data. Similarly, a significant amount of computational power, storage, and processing capacity is needed. AI algorithms should be employed to compute big and sophisticated data continuously transmitted via sensors. Based on historical data, the algorithms are used to suggest actions that should be taken. The digital twin should be able to learn from historical data to improve the performance of the product or asset. Therefore, machine learning algorithms can be utilized to test different scenarios using "what-if" simulations.

II.4.2 Digital twin in quality monitoring of agri-food products

A virtual replica of a product, such as fresh horticultural produce, is known as a digital twin. Sensors that provide data on the environmental conditions near the target fruit or vegetable connect this twin to the real-world product. As a key enabling tool of Industry 4.0, the application of the digital twin in risk management in the supply chain is attracting the attention of the scientific community. Research (Barykin *et al.*, 2020) has identified two types of risks that can disrupt supply chain stability due to faults in their operation. The first type of risk is related to an operation that can result from uncertainties in supply and demand as well as impeded information flow. The second risk results from natural incidences where normal operations in the supply chain are interrupted. Such disturbances in the supply chain can be solved using analytical optimization and dynamic simulation technologies that can improve stability and reliability. By simulating different scenarios, the impacts and risks on the supply chain can be observed using the supply chain digital twin. Thus, the application of the digital twin in the food supply chain can play a central role in solving logistic challenges and sorting and redistribution of food items close to their expiration or quality loss. The digital representation and information of each product can be stored on the IoT cloud to monitor the status and communicate with the end-user through different interaction platforms using smartphones, RFID readers, smart shelf technologies, etc. Therefore, the stakeholders will have a clear picture of the content in the inventory and facilitate the identification of eligible items for transfer before discarding them.

Meeting the ever-changing demand, road conditions, and delivery of perishable items to customers is still a critical question in logistics. These challenges can be solved by utilizing real-time data coming from supply chain agents, including fleets, distribution centers, and consumers. With the development of transformative tools like AI, advanced analytics, and the IoT, competitiveness in companies is being improved, and the supply chain is showing scalable and sustainable growth in business. Moreover, the digitalization of the supply chain is empowered by the development of fields including machine learning, cloud connectivity, IoT, and data interpretation software. A digital twin is among the enabling tools of Industry 4.0 that can utilize transformative technologies. In the supply chain context, a digital twin is considered a dynamic, real-time, and time-phased representation of various actors in the supply chain network. It is a detailed simulation model of an actual supply chain that uses real-time data and snapshots to forecast supply chain dynamics. In this regard, its application can enable the extraction of critical insights and the identification of upcoming problems in real-time.

II.4.3 Application of digital twin in the agri-food supply chain

To ensure the smooth operation of complex logistics systems, a supply chain's digital twin makes use of a streaming data software technique. Each data source can be tracked, and the digital twin contains application codes that enable data analysis. The model adapts to environmental changes and can provide more accurate feedback to data sources when it observes them. For instance, users can create a digital twin for their business using business data, contextual data, numerical simulations, or sensor data. It takes a lot of data to train a digital twin model, and it should be done on cloud platforms that are divided into three distinct components: the physical object, the virtual object, and how they connect (Barykin *et al.*, 2020). The tool utilizes these three components to provide real-time monitoring, visualization, and testing of "what-if" scenarios, allowing users to forecast outcomes before the occurrence of a risk. At its core, the digital twin of the supply chain is based on geographic information system (GIS) technology, which is used to create maps. In the supply chain domain, a digital twin is "a virtual replica of the real process operation which is connected to the real world by sensor data and advanced big data analytical tools "(Verboven *et al.*, 2020).

A digital twin is critical in food supply chain networks because it enables the detection of risks in advance and the prediction of delivery times and routes based on GIS data, such as how long it will take to receive the food. This is a sophisticated tool that can capture real-time data and create a map-based virtual replica of the natural world, combining various types of data into a single view that users can easily access. Barykin et al. (2020) demonstrated the use of GIS-based cold chain management in the transportation and distribution of fresh products under temperature control. The proposed methodology incorporates vehicle routing, and various scenarios have been evaluated in terms of fleet size and distribution centers, total travel time and distance traveled, and so on. New research demonstrates how delivery routes can be optimized when real-time data and multi-objective genetic algorithm optimizers are used (Tsang *et al.*, 2021). This is a significant step toward controlling dynamic supply chain events that result in food spoiling before it reaches customers or end-users. When it comes to real-time vehicle tracking and automatic data collection, IoT technologies are the most prevalent. This means they can assist businesses in optimizing delivery schedules. Thus, individuals will be able to observe the delivery process and their ability to handle orders.

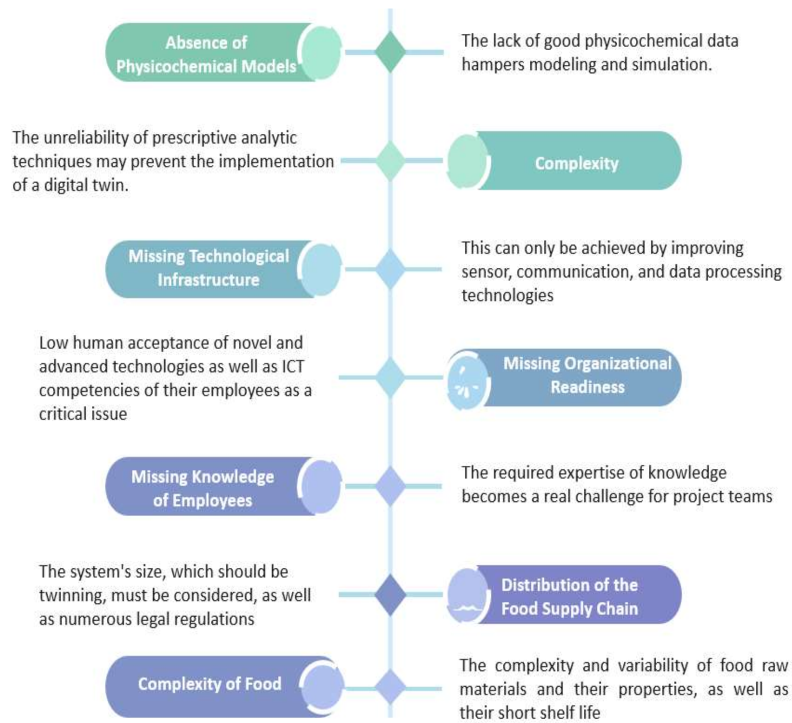

Figure II.14 *Digital twins implementation challenges in the food industry (Henrichs et al., 2022)*

Coordination is another significant benefit gained from supply chain digital twin applications. Lee and Lee (Lee and Lee, 2021) demonstrated a digital twin framework for supply chain coordination through the use of real-time logistic simulation. The virtual asset was created and simulated using various logistics scenarios and a routing application. The digital twin was updated with the help of building information modeling and IoT sensors to gain insights and consistently realign with customer satisfaction plans. The full range of technologies required to create a supply chain digital twin model is comprised of a combination of simulation modeling, optimization, and data analytics (Barykin *et al.*, 2020). This model is linked to an online data flow and is suitable for risk management. By simulating and planning scenarios, it is possible to observe the effect on supply chain productivity of various supply chain failures and recovery policies. By modifying the digital twin model of the supply chain, it is now possible to visualize how the physical supply chain operates, although the challenges remain for implementing digital twins in the food business (Figure II.14).

In general, as public health concerns, logistical complexity, and perishability have increased (Ahumada and Villalobos, 2009), the supply chain for fresh produce has received considerable attention. Other significant issues in the agro-food supply chain include demand and price volatility, product quality, and weather variability (Salin, 1998), all of which contribute to the overall value chain's optimization (Keates, 2019). As an enabler of Industry 4.0, the digital twin can increase the visibility of customer demand estimates, order tracking, and other real-time data, enabling real-time decision-making (Asadollahi-Yazdi *et al.*, 2020). It also provides proactive capabilities like continuous stock monitoring and active replenishment plan, as well as early detection of supplier quality issues and real-time safety monitoring. Digital twins can help with decisions, communication, scheduling and planning, logistics management, warehouse management, and other duties in the food supply chain (Henrichs *et al.*, 2022).

Chapter III
Digital twin application in the monitoring of fruit quality changes

III.1 Introduction

Food waste is a big problem for environmental, economic, and food security reasons. Around the globe, the volume of food waste is estimated to be 1.6 billion tonnes, of which 81% of this amount is in acceptable conditions for human consumption (Godoy *et al.*, 2014; FAO, 2018). Fresh fruit and vegetables have been identified as the main contributors to the amount of wasted food. Research showed that while fruits and vegetables comprised a whopping 85% of food waste by mass, they only contributed to 46% of the wasted carbon footprint (Scholz, Eriksson, and Strid, 2015). For instance, only in Italy, 34% of the total wasted weight at the retailer level is from fruit and vegetables. Apples, lettuce, pears, bananas, peppers, grapes, sweets, and tomatoes are fruits and vegetables in "hotspot categories", contributing to most of the waste (Scholz, Eriksson and Strid, 2015). As a part of this category, bananas are among the most commonly wasted fruits where the effects of handling and storage have a severe impact on the appearance quality of the fruit by causing brown to black discoloration of the skin, called a bruise.

As described in the introduction, the emphasis of this research will be on a very perishable food category, namely fruit. Retailers or suppliers currently lack real-time visibility into the status of fruits in their inventory, resulting in significant fruit. The use of digital twin technology to monitor the condition of fresh fruit is thought to be a promising tool. The use of mechanistic models to develop fresh produce digital twins that simulate the thermal behavior of fresh produce throughout the cold chain using measured temperature data is mentioned in the report (Defraeye *et al.*, 2019). Finding an appropriate data acquisition system for fruits, on the other hand, remains a challenge. Techniques for monitoring, controlling, and predicting the quality of fruits and vegetables in agri-food supply chains have been developed in recent decades (Onwude *et al.*, 2020). There are a variety of methods employed, including imaging systems, spectroscopy, multiple sensors, printed sensors, the acoustic impulse response, the E-nose, RFID, and mathematical modeling. Image analysis techniques used in the food industry provide benefits such as objectivity, continuity over time, and quick decision-making (Hassan *et al.*, 2012). The imaging technique is highly useful in detecting and evaluating the characteristic features of a product's quality.

Several reports have recently been published on the use of IoT technologies in smart farming and post-harvest. Many of these inventions, however, are not described as digital twin applications. The current trends of the digital twin in postharvest supply chains have been reported in detail by the report (Defraeye *et al.*, 2021). There is also evidence to suggest that images of crops and other agricultural products can be used to apply machine learning and deep learning techniques. For example, Baranowski and his colleagues (Baranowski *et al.*, 2008) reported on the potential use of optical sensors in the inspection of vegetables, fruits, and crops using machine learning approaches in the agri-food business. Similarly, generic algorithm approaches based on neural networks have been used to identify different cherry tissues (Villacrés and Cheein, 2020). Another study found that using neural network classifiers to grade banana fruit was effective (Hussein, Fawole and Opara, 2020). This research has indicated the possibility of implementing the outcome in the sorting of banana fruit in manufacturing plants. Krishnan, Sofiah, and Radzi (2009) proposed the use of neural networks in the determination of banana ripeness by using RGB color components of the banana captured daily until its full rotting. According to reports, machine learning has produced superior results in agricultural applications such as image classification (leaf picking) by robotic systems (Ahlin *et al.*, 2016) and fruit detection, segmentation, and counting (Chen *et al.*, 2017). Deep learning, in particular, is effective in image classification, making the technique more appropriate for detecting internal fruit defects.

Any virtual representation of an item, a product, or an asset is referred to as a "digital twin" (Marmolejo-Saucedo, Hurtado-Hernandez, *et al.*, 2020). It connects a physical entity to its virtual counterpart (Melesse, Di Pasquale, and Riemma, 2021), allowing simulation, analysis, and control. It is a dynamic software simulation model of a thing or system that uses data from a sensor to understand its state, respond to changes, and improve operations. In post-harvest, a digital twin is defined as a virtual representation of fresh horticultural produce that contains essential components and material properties that are linked to the real-world product and processes via sensor data, preferably continuously updated in real-time throughout the product's life-cycle (Defraeye *et al.*, 2021). It realistically represents a fruit, mirroring its behavior, allowing one to track the status of the fruit based on the level of product defect.

The purpose of this chapter is to propose a method for creating a digital twin of fruit using a thermal camera as a data source. The proposed solution is intended to assist retailers and other stakeholders involved in the fruit supply chain by increasing the visibility of their inventory. It also describes how a deep convolutional neural network (CNN) is used in the development of a machine learning-based digital twin. The chapter is structured as follows: The related works are described in Section 2. Section 3 describes the model architecture and implementation. Section 4 presents the research approach, and finally, Section 5 describes the details of the model evaluation.

III.2 Related works

III.2.1 Use of digital twin in product quality monitoring

A digital twin is one of the promising technologies for utilizing intelligent data in the food supply chain. In theory, digital data can be intelligent when used to monitor and predict the underlying process. The trend of utilizing such types of data in the food supply chain is still limited.

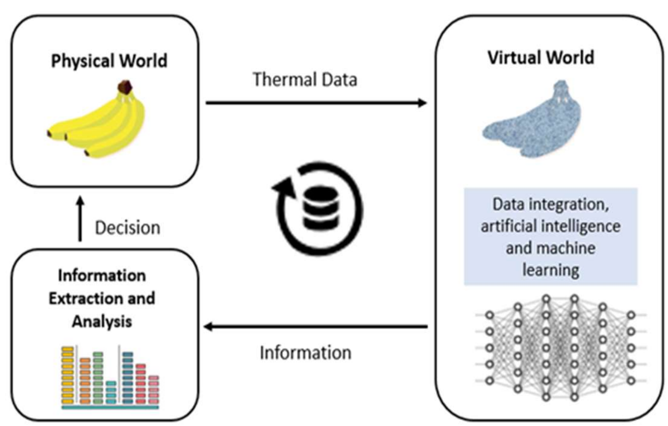

Figure III.1 *The digital twin of fruit produce*

The application can assist in reducing inter-product diversity, improving shelf life and quality, minimizing wastes, saving resources, improving maintenance activity, lowering costs, optimizing production planning, improving logistic service, saving energy, and increasing transparency.

Developing a digital twin of food products (Figure III.1) is still in its early stages. Siemens, one of the leading companies in the application of digital twin, has proposed the development of a digital twin of food products that includes all information about ingredients, receipts, production processes, status, and location to ensure food security, sustainability, and reduce environmental pollution risks (Southey, 2019). Similarly, a new study by (Urbina, Daniel Barahona, José Ordoñez Castillo, Ana Alicia Paz de Galindo, 2021) proposed a solution to monitor and detect physical damage to fruits during the supply chain process, where 20% of product damage occurs. In this context, an IoT platform service was created to generate predictive insights that can aid agricultural producers' and exporters' decision-making processes by reducing waste. The system employs fruit-shaped devices (digital twins), which mimic the physical properties of real fruit. This device travels with the fruits during transportation and collects all information via sensors. The data is processed by the IoT cloud platform to detect process failures and forecast future product damage. The post-harvest sector has seen recent advancements in the use of digital twins (Defraeye *et al.*, 2019; Verboven *et al.*, 2020). For example, food traceability, supply chain logistics, and food safety could all benefit from the use of digital twins in a wide range of industries.

III.2.2 Real-time data acquisition tools for fresh foods

Recently, with the advancement of imaging techniques, thermography technology has attracted food science and technology researchers. It is one of the most common non-destructive quality control strategies used in industry. On the market today are inexpensive wireless sensors for monitoring food processing conditions such as gas concentration, light, flow rate, stress, temperature, humidity, and pressure (Chaudhuri *et al.*, 2018). Because of their flexibility, low cost, and small size, non-destructive sensors such as electromagnetic spectrum, spectroscopy methods, and imaging are becoming more popular in the monitoring of food products (Onwude *et al.*, 2020).

Thermal imaging is emerging as a tool for assessing food quality and safety in the food industry (Ferreira, 2020; Dong *et al.*, 2022). Surface detection is the most common application of machine vision in postharvest supply chains. However, the use of thermal data in image classification aims to identify objects that have certain characteristics, including internal defects. Some of the applications include temperature monitoring and validation in food applications, postharvest quality control, grain quality, and foreign body detection. However, limitations in the application of thermal imaging must be overcome before its widespread use in online food monitoring. One issue with using this tool is the temperature contrast created during the heating or cooling process. A uniform spatial distribution of temperature is required for the thermal camera's view to producing a more reliable thermogram. Temperature inference from the environment is another challenge in the use of these sensors. As a result, adequate environmental temperature control is required to eliminate non-uniform image backgrounds, which leads to incorrect decisions.

The majority of imaging techniques, except for infrared thermal imaging, have some drawbacks, such as the need for artificial lighting during image capture and the inability to detect internal characteristics (Onwude *et al.*, 2020). Controlling the level of bruises with infrared thermal cameras is a notable way to overcome this challenge. A bruise is damage to fruit tissue that results in physical or chemical changes in color, smell, and taste, as well as spoilage. Physiological and biochemical properties, as well as environmental conditions such as temperature, humidity, and a variety of other postharvest treatments, all, influence the extent of bruising, and the risk is greatest in matured fruits (Hussein, Fawole and Opara, 2020). Fruit that has been stored for a long time may be more susceptible to bruising or tissue damage (Zeng *et al.*, 2020).

Thermal imaging is a new non-contact technique that is commonly used for fruit safety and quality assessment in the fruit and food industry (Abasi *et al.*, 2018; Zeng *et al.*, 2020). It can keep track of a product without having to take a sample, which could result in permanent damage. Temperature differences between bruised and healthy tissues are detected using infrared thermal imaging due to differences in thermal diffusion coefficients (Veraverbeke *et al.*, 2006). The detection of heat emitted by an object in the form of infrared radiation is possible with this technology. Electrical signals and images are generated by this radiation (heat map). Because damaged cells beneath the skin become filled with water, fruit with bruises has a lower reflection. As a result, infrared radiation passes through the skin and reaches the water accumulation, where it is absorbed more strongly than in undamaged fruit flesh. In thermal images, the bruises appear darker than the undamaged parts of the same fruit, resulting in contrast. More interestingly, thermal image detection works well at all brightness levels, allowing the targets to be easily distinguished from the background depending on the radiation difference. This method is extremely effective at detecting bruises before they are visible to the naked eye. Thermal images taken in specific ranges make it easier to distinguish between areas that have tissue problems and areas that are healthy (Baranowski *et al.*, 2009).

Mechanical damages, physiological disorders, morphological disorders, pathological disorders, and internal defects are all common types of defects in horticultural products. Internal defects are potential problems that can occur throughout the food chain. As a result, the ability to reduce fruit and vegetable loss and waste is dependent on the accurate detection of these disorders.

Fruits are high-risk food items due to the difficulty in monitoring their defect level during storage. The use of thermography in fruit detection has been reported as a promising solution. According to a study (Hajalioghli, 2020), active thermography is effective in the detection and classification of apple bruises. The temperature difference between bruised and sound tissue has been suggested as a basic criterion for classifying the fruit. Gurupatham, Fahad, and Hudlow (Gurupatham, Fahad and Hudlow, 2018) used thermal images to demonstrate the different ripeness levels of avocados.

Table III.1 *Some of the applications of thermal imaging in fruit detection*

Purpose of application	Result	References
Control the citrus surface drying	○ Allows to determine the moment when the surface drying finishes and the peel drying begins	(Fito *et al.*, 2004)
To detect water core in 'Gloster' apples	○ Able to distinguish affected and unaffected apples	(Baranowski *et al.*, 2008)
To detect early apple bruises in the apple sorting process	○ Systems are not capable of effectively distinguishing fruit with bruising which occurs a short time before the inspection	(Baranowski *et al.*, 2009)
Surface quality evaluation of apple	○ The surface quality differences resulting due to wax were easily evaluated based on surface temperature	(Veraverbeke *et al.*, 2006)
Defect detection on cherries, classification, and counting.	○ Able to detect cherries with 85% accuracy and to estimate production with 25% error	(Villacrés and Cheein, 2020)
Detection and classification of bruises of pears	○ The best test prediction accuracy obtained was 99.25%	(Zeng *et al.*, 2020)

III.2.3 Machine learning techniques in the monitoring of fruit status

Manual fruit status monitoring by operators is costly, tedious, laborious, and inherently unreliable due to its subjective nature. As a result, the use of thermal imaging and deep learning techniques in this area can be viewed as a novel approach to reducing time and cost while improving detection accuracy (Villacrés and Cheein, 2020). The use of thermography in agronomy plays an important role in detecting changes in plant conditions in real-time. The potential use of thermography for the surface temperature of plants under stress conditions, the detection of plant disease, crop yield estimation, and plant phenotyping has been described in a report by Messina and Modica (2020). There is evidence to suggest that images of crops and other agricultural products can be used to apply machine learning and deep learning techniques. For example, Villacrés and Cheein (Messina and Modica, 2020) reported on the potential use of optical sensors with machine learning approaches in the inspection of vegetables, fruits, and crops. Similar to this, banana fruit classification using neural network classifiers becomes quite successful (Olaniyi, Oyedotun and Adnan, 2017).

Patterns in the images captured by infrared thermal cameras are used to classify images using thermal images. This type of classification frequently employs both supervised and unsupervised machine learning techniques. The majority of supervised machine learning is based on training inputs and desired outputs (called "labels"). It requires that the data be labeled so the software can learn when it is right or wrong. Unsupervised machine learning, on the other hand, does not provide labels to the learning algorithm, leaving it to find structure in its input on its own. unsupervised learning only needs raw data for grouping things or associated things together, as it is used in a recommendation system, for example, by Netflix or Amazon. These techniques are becoming more effective, and their use in image processing and classification has skyrocketed.

Machine learning can provide efficient methods for acquiring data, processing images, and classifying thermal data. It has been reported that the use of machine learning has produced superior results in agricultural applications such as image classification (leaf picking) by robotic systems (Ahlin *et al.*, 2016), and fruit detection and the technique has become more suitable in the detection of internal defects in fruits.

III.3 Model architecture and implementation

The SAP cloud platform was used in this work for training purposes with historical data. Deep neural networks and advanced predictive modeling capabilities are used in the framework.

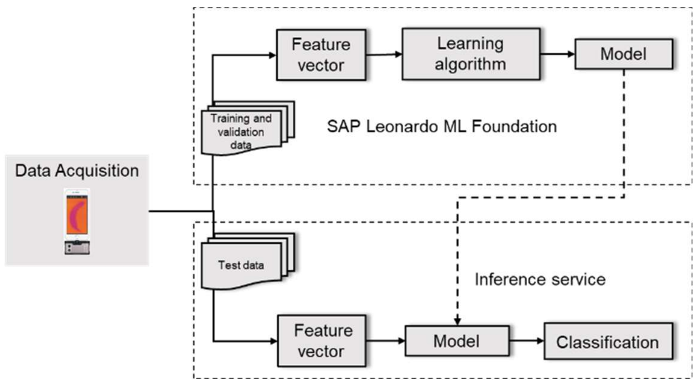

Figure III.2 *Workflow of the training process*

The algorithm was tested during the training and inference stages of this implementation (Figure III.2). The learning stage is where the data is described and a trained model is built. The image must be transformed into a vector representation during the learning process. A learning algorithm selects a model and quickly searches for the parameters of the model.

The trained model is used in the inference stage to make predictions about new data. The process employs feature vectors as a representation of real-world data that the training and inference components can use. It is the process of testing the model's performance on new data for the model to provide the final predictive power. This is equivalent to using the model in real-world scenarios. In the case of a digital twin, real-time data captured by the thermal camera will be used.

III.4 Research approach

The fruit digital twin was created using the infrared thermal camera as a data acquisition tool to evaluate product quality based on temperature changes related to a product defect. The thermal camera's images were used as an input dataset for CNN training. These images use machine learning to provide underlying physiological information on the status of fruit, which can offer a test for the accuracy of prediction. Deep learning, in particular, has been used for classification purposes based on patterns of images resulting from contrast. A supervised type of machine learning technique was used in this training. This machine learning technique is primarily based on training inputs and desired outputs (called "labels"). This technique is becoming more effective, and its use in image processing and classification has surged.

III.4.1 Collection of the dataset

Images captured with the FLIR One thermal camera were used to create the dataset. The images were collected at various stages of storage time to study the quality evolution. Before beginning the training process, the dataset of fruit images was graded into four categories: "fresh," "good," "bad," and "rotten" (Figure III.3).

Figure III.3 *Four classes of the dataset used during the training of the model*

III.4.2 Training and deployment of the model

Images captured by a FLIR one thermal camera were used to create the dataset. The images were collected at various stages of storage time. This fruit dataset was divided into four categories. Based on traditional approaches used in the retailers, the thermal images were labeled as “fresh”, “good”, “bad”, or “rotten”. According to this proposal, fresh is assigned to fruits that can fully satisfy the interests of customers, while fruits that are predicted to be good retain their market value and force retailers to provide some discounts. On the other hand, because banana fruit has a high level of wastage, retailers can donate to charity organizations to save the lives of poor people. After all, if proper follow-up is not implemented, the fruit is at risk of being wasted, which in this case is rotten fruit.

To train the dataset in the SAP Leonardo ML foundation, the entire dataset was divided into 80-10-10 folders for training, testing, and validation. Each category contains four labels. In the SAP cloud platform, the training process involves mainly five processes: the creation of a service instance; uploading the data to the file system; training the model using the uploaded data; deploying the trained model to the service instance; and testing.

In the testing of a predictive model, TensorFlow is a powerful deep neural network architecture that has been used in SAP's intelligent technologies. It is a popular machine learning framework that has been open-sourced by Google. Deep neural networks and advanced predictive modeling capabilities are included in the framework.

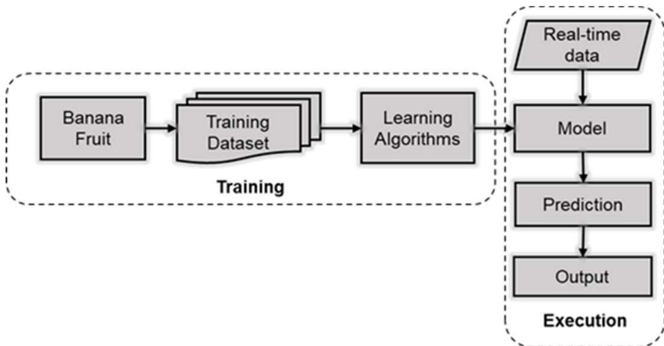

Figure III.4 *Model training and execution process*

The concept of a digital twin can be implemented after it has been trained by injecting data into the trained neural network (Figure III.4). As a result, the prediction will be carried out based on historical data stored in the SAP Document cloud storage, and end-users will be notified about the product's status.

III.5 Model evaluation and performance

CNN is a type of multi-layer neural network (Figure III.5). It is a well-known feed-forward network capable of extracting topological information from an image. They can be trained to recognize patterns in images using the back-propagation algorithm. All neurons in a feature have the same weights in feature extraction (but not the biases). The steepness of the activation function is determined by weight. It increases the steepness of the activation function and determines the speed of triggering for the function, whereas bias is a constant that assists the model in fitting the given data as best as possible. Accordingly, all neurons detect the same feature at different points in the input image.

The convolutional layer is considered the core building block of the neural network aimed at feature extraction in CNNs. The layer is made up of a collection of learnable filters (kernels) that are used to recognize patterns in images. Convolution works by sliding the filter over the input image and taking the dot product of the filter and chunks of the input image. The pooling (subsampling) layer reduces the size of the feature maps by summarizing sub-regions using some functions, and each grid will generate a value. This layer manages overfitting by sliding a window across the input and feeding the window's content. As a result, the primary goal of pooling is to reduce the number of parameters in the network while also making learned features more stable by making them more resistant to changes in scale and orientation.

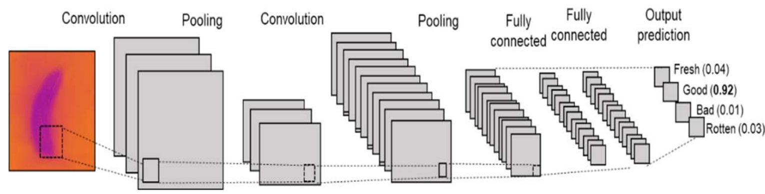

Figure III.5 *Principle of Convolutional Neural Networks*

The fully connected layer is fully connected to the previous layer's output. It connects all of the neurons in the previous layer to every single neuron it has. Including a fully connected layer is another method for learning non-linear combinations of these features.

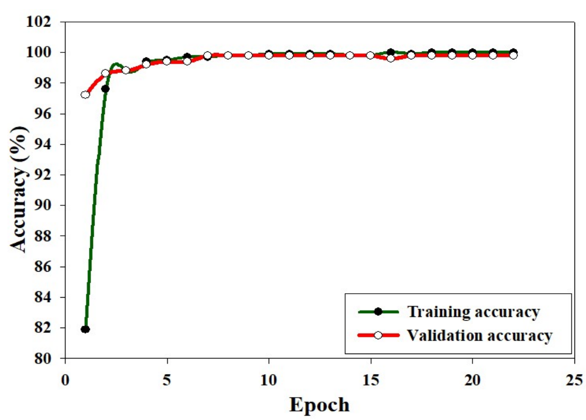

Figure III.6 *Training and validation accuracy of the retrained model*

Following training, the model is found to have a summary of batch size, learning rate, the total number of training epochs, best accuracy, final test accuracy, prediction of top classes, and the starting and lasting time of training, as described in Table III.2. The model was trained over 150 epochs. However, no improvement was found after epoch 21. This was followed by model testing with various new images, which yielded a positive result. This is part of the model evaluation following the completion of the training phase, which successfully predicted the fruit status.

Figure III.6 depicts the training accuracy as the percentage of the current dataset's data labeled with the correct class, while the validation accuracy illustrates the precision of randomly selected images from a different class.

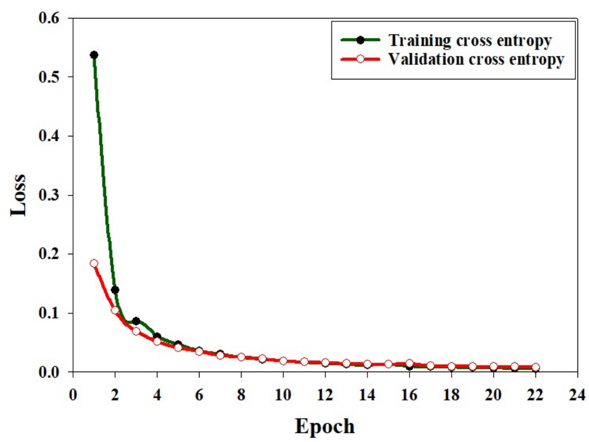

Figure III.7 *Cross entropy loss of training model*

The main goal of learning is to minimize loss as much as possible. The accuracy increased from 0.26 to 0.99 during training, which is a significant improvement. Similarly, both the training and validation values of cross-entropy loss have decreased.

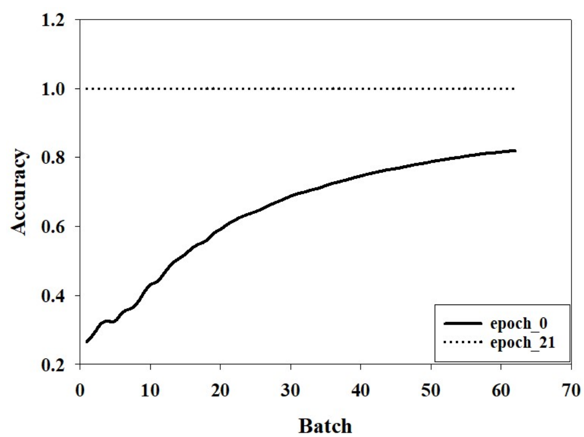

Figure III.8 *The trend of accuracy for the initial and the last epoch*

The end of training output promises results with an average training accuracy of 100 percent and a validation accuracy of 99 percent, indicating that the image classifier performs well. Both the accuracy and loss curves show some overfitting, as shown in Figure III.6 and Figure III.7, but the performance is not degraded. The overfitting issue could be caused by using a training dataset with similar patterns. Although the model learned the details and noise in the training dataset, this can sometimes degrade the model's performance with new data. However, based on the trends in the graphs, it is possible to conclude that the model is good because of its high accuracy and low loss. As a result, it can capture the dataset's underlying logic.

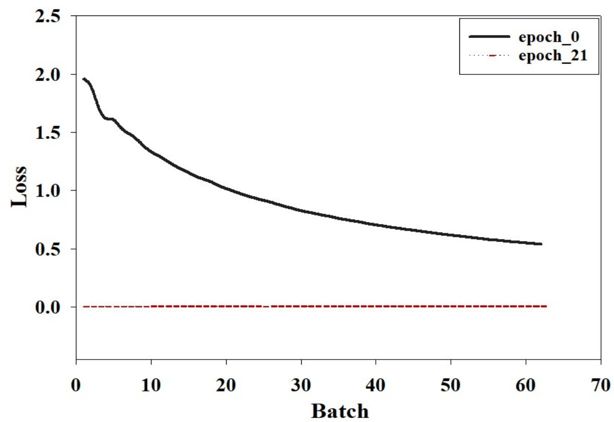

Figure III.9 *Comparison of cross-entropy loss for epoch_0 and epoch_21*

The loss function computes the difference between the predicted and actual values of the training data, whereas the accuracy function compares the classified image to another data source, which is ground truth data. Another important factor that can influence neural network convergence during training is the learning rate. It has a large influence on epochs. As a result, a low learning rate causes the training process to converge over several epochs and vice versa. An optimized learning rate was used in this training.

The training loss and accuracy were found to be 0.005 and 0.99, respectively, while the corresponding values for the training and validation cross-entropy loss were 0.005 and 0.008, indicating that the targets are not far from predictions. Figure III.9 shows that with a learning rate of 0.001, the loss has decreased from 1.95 (batch 0 of epoch 0) to 0.005 (batch 21 of epoch 61). Figure III.8 shows the improvement in accuracy as well.

Table III.2 *Training summary*

Properties	Value
Training batch size	64
Learning rate	0.001
Total training epoch	150
Stop after no improved epochs	15
Epoch with the best accuracy	6
Best validation accuracy	0.99
Predicted top classes	4
Final test accuracy	0.99

In general, this research aims to close a technological gap in the agri-food supply chain that monitors the evolution of fruit quality, resulting in massive fruit waste. A digital twin is a promising tool for reducing fruit waste by monitoring and predicting the status of fresh produce throughout its life. The use of a thermal camera allows it to detect surface and physiological changes in fruits during storage. The use of a deep convolutional neural network to monitor the fruit status yielded promising results. Thus, the use of thermal imaging techniques in conjunction with machine learning techniques would bring about a new paradigm in the fruit supply chain.

Chapter IV
Digital twin for inventory planning of fruits

IV.1 Introduction

Food distribution is most likely one of the earliest commercial activities documented in human history. While the food sector is by no means new, it requires cutting-edge technology to remain competitive in today's challenging business climate. The sector can be enabled by cloud computing and driven by Big Data technologies to improve inventory forecasting that is specifically suited to optimize fresh food inventory. Therefore, companies can enhance their service quality by minimizing the amount of both the stock-outs and perishable commodities in stock. This will reduce food waste and guarantee that customers receive even fresher goods.

Perishable food needs special attention due to its biological composition and supply chain uncertainties. Forecasting the elements of the food supply chain has proven to be a vital process. Improper tracking and control of inventory levels can result in the loss of a large amount of food, which might benefit millions of people in need of food. The maximum amount of food is lost in the fruits and vegetable supply chain as a result of poor quality and supply-demand mismatches (Raut *et al.*, 2019). According to the study, the supply-demand mismatch is driven by both internal and external causes, including government policy, a lack of retail facilities, awareness, and transit infrastructure (van Donselaar *et al.*, 2006).

Food waste can occur when products are still usable but approaching the end of their life. This problem occurs due to a lack of synchronization in the demand and supply of the products. Developing solutions for this type of problem is regarded as a critical step toward inventory management because it helps to alleviate issues related to fruit loss due to the mismatch between supply and demand in the marketplace.

In the past decades, various technologies have been implemented to improve the efficiency of the perishable food supply chain. Some of the technologies include radio frequency identification, the Internet of Things, blockchain, three-dimensional printing, autonomous vehicles, and unmanned aerial vehicles (Morrison, 2009). These technologies have increased the efficiency of the system. However, they are unable to reduce food waste to the extent that was anticipated. The use of reliable simulation-based digital twins can be considered one of the key approaches to monitoring inbound and outbound logistic processes in real-time.

By definition "a supply chain digital twin is a detailed simulation model of an actual supply chain which uses real-time data/snapshots to forecast supply chain dynamics" (AnyLogistix, 2020). Analysts can use the output to understand the behavior of a supply chain, predict abnormal situations, and propose an action plan. A digital twin is one of the industry 4.0 enablers that allow for deep synchronization and dynamic interaction between the physical and virtual worlds (Wang, Wang and Liu, 2020). Companies can use Industry 4.0 to improve interoperability, data transparency, technical support, and decentralized decision-making. To analyze and predict changes in real-time data about orders, supply, demand, approvals, etc., a supply chain uses a digital twin. The data is collected by IoT devices (sensors), databases, users, and vendors. So, companies can better track their supply chain and react quickly to changes.

Producers, distributors, and retailers can benefit from accurate and timely forecasting of future supply and demand in today's highly competitive and frequently changing business environment. Because many food items have a short shelf life, accurate forecasting is critical, resulting in economic damage in both shortage and surplus cases (Tsoumakas, 2019). In this rivalry, technological solutions that can continuously control demand can be a valuable tool in understanding how demand evolves and developing more accurate forecasts. Machine learning is one way for improving the accuracy of demand forecasts. It's a method for forecasting the future based on recurring patterns uncovered through iterative data learning.

Supply chain management is full of trade-offs, and one of the most challenging issues is the balance between demand and supply. Forecasting is the most common yet least understood activity in operations management that could eliminate or at least clarify the uncertainty surrounding a future event or series of occurrences. It is used to evaluate a data series to predict one or more future periods, and it allows an estimate of the degree of error that can be conveyed in the forecast. Because they allow enterprises to correlate different data streams and standardize the information, digital twins are a good fit for automation and feeding time series data into time series insights. Inventory forecasting, which is also referred to as demand planning, is the act of anticipating inventory levels for a future period based on historical data, trends, and known upcoming events. Forecasting accurately ensures that businesses have enough products on hand to fulfill client orders while not wasting money on excess inventory. Forecasting is the analysis of data to identify patterns and trends that can be utilized to adapt to changing conditions and meet client demand.

In digital twin development, the use of accurate time-series and predictive Analytics tools provide insights about future events. Forecasting is at the core of supply chain planning, and the outcomes are crucial in coordinating sourcing, production, and logistics (Wang, Wang and Liu, 2020). Using forecasting techniques, the model can provide insights into future phenomena based on trained historical events. The use of precise time series prediction can be used as an important tool in constructing a digital twin (dos Santos *et al.*, 2020; Hu *et al.*, 2021). Therefore, through digital twin-led data integration, the stakeholders can get constant support from the system using real-time or near real-time data.

The chapter proposes the use of a time series-based digital twin in forecasting and the continuous decision-making process for planning perishable food inventory operations. For training the model, historical data of inbound and outbound logistics was used from the food bank database and implemented in SAP Analytics Cloud. Section 2 provides related works and the theoretical background of time series-based digital twins in supply chain planning, which is followed by the proposed approach in section 3, and section 4 describes the case study of the Italian food bank.

IV.2 Related works and theoretical background

Nowadays, supply chains are transforming themselves from traditional sequences to digital supply chain networks that can allow using of information from different sources during production and distribution phases. As a result, companies can provide synchronized scheduling, dynamic execution, intelligent supplies, monitor connected clients, and create a smart factory (Barykin *et al.*, 2020); therefore, creating a more responsive environment for all stakeholders.

In the perishable food supply chain and saving the loss of food products, planning is the foundation for productivity, quality, and overall effectiveness of the supply chain network (Wang, Wang and Liu, 2020).

As a novel technology, the digital twin can synchronize the real and virtual environments in the supply chain by merging data from many sources, such as supply, demand, product quality, and planning variables. Moreover, the digital twin paradigm can be used to link transportation management, supply chain management, ERP, business intelligence, demand forecasting, production planning, and inventory management. Forecasting, in conjunction with other approaches such as simulation, time series, qualitative, and informal methods, builds the foundation for supply chain digital twin creation (Wang, Wang and Liu, 2020). The application of these methods will answer questions about planning issues, including the quantity to be purchased, delivered, or produced. In particular, the time-series method of forecasting looks at the trends in historical data.

The use of simulation with forecasting methods can provide insights into certain supply chain phenomena. There are many use cases for time-series-based forecasts in operational planning (dos Santos *et al.*, 2020; Hu *et al.*, 2021). However, to be a digital twin, the forecast should provide constant decision support and integration with the virtual model. In the definition of a digital twin, it is common to see the term "real-time" and the use of sensors. But in the case of the supply chain, real-time might not be critical (dos Santos *et al.*, 2020). The time scale of a digital twin is dependent on the type of goal. For instance, distributed control systems, model predictive control, online optimization, and process scheduling use time scales of seconds, minutes, hours, days, or weeks, respectively. In addition, data collection using sensors might not be possible or feasible, and commonly, manual processes are more appropriate.

In perishable food inventory management, forecasting will help to plan the amount of inventory level in response to different constraints such as storage space and product shelf life. The accuracy of these forecasts can be improved using tools of industry 4.0, such as big data analytics. The development of a supply chain digital twin starts with mapping the process and determining the data source of the supply chain network (Figure IV.1). Then, using IT architecture, the internal and external real-time data sources will relate to the model of the supply chain that can enable simulation, optimization, and analysis of a system. In this way, machine learning is an important tool to use to learn about the system, test different scenarios, or respond to problems in the supply chain network.

The concept of the "digital twin" has gained popularity in supply chain management in recent years. The study by Marmolejo-Saucedo et al. (Marmolejo-Saucedo, Retana-Blanco, *et al.*, 2020) has proposed a digital twin approach for an automotive company in Mexico to improve delivery times to customers. In this case study, the authors used anyLogistix supply chain software to develop a digital twin for decision support using enablers such as flexibility, agility, and real-time data exchange. Besides, a report has proved the application of digital twins in logistics networks as a non-destructive quality control method compared to traditional methods (Kapustina *et al.*, 2020). The article also discussed the main differences between traditional and digital supply chains.

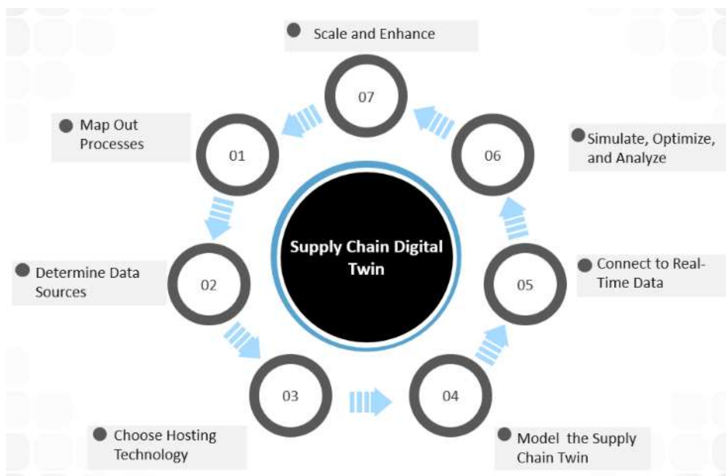

Figure IV.1 *Steps to supply chain digital twin (Coupa, 2020)*

Despite that, the implementation of digital twins has adverse effects on companies' business and visibility. Common obstacles to the successful implementation of digital twins include education (which causes management change and knowledge transfer), accurate representation, data quality, costs, IP protection (data ownership concerns, identity assurance procedures, and user access control), digital security, and interoperability (Moshood *et al.*, 2021; Kamble *et al.*, 2022). In the case of the agri-food domain, the application of digital twins is still at an early stage due to ethical issues and societal and safety impacts they may bring (van der Burg *et al.*, 2021). However, reports are showing promising signs of progress in the sector (Verboven *et al.*, 2020; Agrawal *et al.*, 2021; Pylianidis, Osinga and Athanasiadis, 2021).

IV.3 Proposed Approach

As described in Figure IV.2, the approach uses operational data to develop a digital twin-based decision support system for fresh fruit inventory. The model leverages the food bank's incoming donations and outbound logistics data to generate insights for rescheduling the delivery process and controlling inventory levels. The approach illustrates the general framework of the supply chain that will be assessed in the next work. However, in this piece of work, we have specifically focused on the use of time-series data. The time series can be automated using SAP Analytics Cloud (SAP, 2022) and the model can be trained using a forecast algorithm. The SAP Analytics Cloud is a user-friendly, web-based platform that makes it simple to define insights, create trends, and combine different parameters using embedded artificial intelligence and machine learning technologies.

Time series forecasting is useful for estimating a measure's future values. The historical data is divided into two sections: 75% of the dataset is allotted for change detection and model generation. The remaining 25% is the validation dataset, which is used to assess the quality of the prediction models and select the best one. The validation procedure compares the actual values of the measure to the anticipated values of each model. This subset is used to calculate the difference between actual and forecasted values over the time horizon specified by the user in the model settings. The difference shows the forecast model's error. The standard deviation from this series of errors is then computed using Smart Predict.

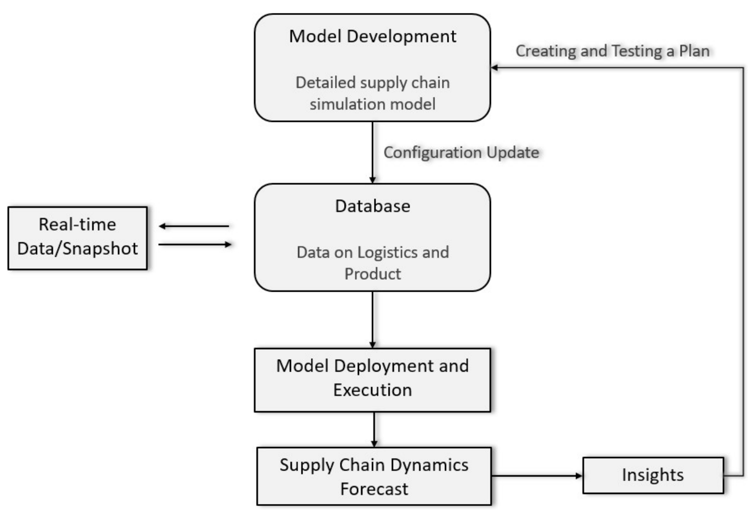

Figure IV.2 *The general framework of supply chain digital twin*

The objective of the proposed framework is to ensure that the food bank has enough fruit on hand to fulfill the demand of small charity organizations while balancing the amount of fruit supplied by different donors (Figure IV.4) and the storage space required to minimize fruit waste.

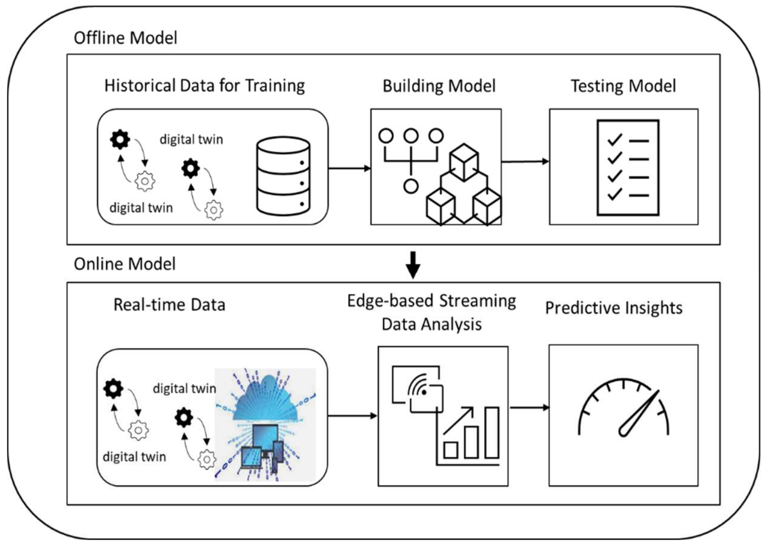

Figure IV.3 *Workflow of a predictive model*

In contrast to traditional simulation models, the proposed model is constantly updated to adapt to the real process. This will provide a continuous decision-aid tool for the supply chain activities of a food bank, to make more efficient decisions and meet demand according to the requirements of the organization.

Figure IV.3 depicts the steps involved in creating a predictive model for a data-driven digital twin using time-series data. Building an offline predictive model and deploying an online predictive model in the SAP Analytics Cloud are the two primary parts of the workflow. Using past operational data, an offline prediction model will be built and trained. Using digital twin-driven real-time operational supply chain data, the proposed predictive model will be utilized to predict potential risks online. These output forecasts will be used by smart prediction to make decisions regarding the level of fresh food inventory.

IV.4 Case Study

A case study of Banco Alimentare Campania Onlus is used to evaluate the proposed approach. It is a non-profit organization that recovers and collects surplus food from different sources in the supply chain, including food processing, agriculture and primary production, distribution, food service, and retail (Silchenko, Simonetti and Gistri, 2019). Banco Alimentare Campania Onlus is among 21 regional food banks operating across Italy. The organization collects food from different donors and re-distributes it to more than 350 small charities located in the Campania region (Figure IV.6).

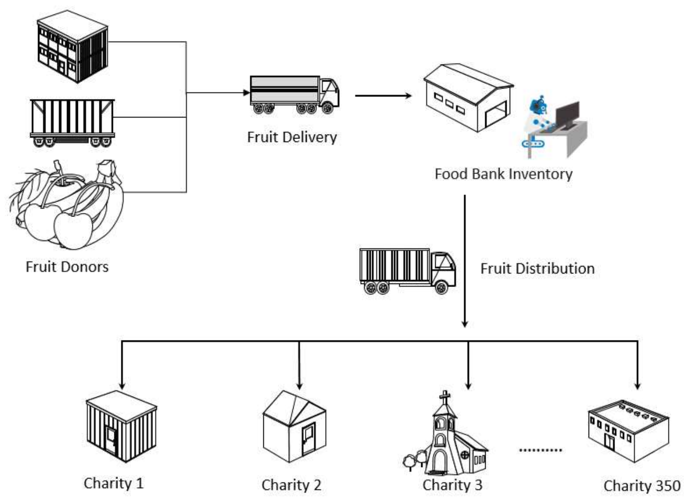

Figure IV.4 *Structure of fruit supply chain network*

Due to uncertainties in demand by charity organizations and incoming donations, the food bank is wasting huge amounts of fruit. This case study has focused on perishable food items such as fruits. In this supply chain network (Figure IV.3), there is uncertainty in the donation and distribution of fruits to charity organizations on an irregular basis. Similarly, orders are coming from different charity organizations operating in the region. The donors usually notify the food bank within 48 hours by mail to ask about the availability of receiving donations. In this case, the food bank does not order the products; it simply receives the items that are offered.

The delivery of the fruit is almost exclusively at the expense of the donor. However, coordination between donors, food banks, and the local charity is poor. Due to such a traditional way of communication, the food bank is facing challenges in managing its inventory to save perishable food items that are going to waste in a short period. The use of a digital twin, therefore, will improve the visibility of the inventory, enabling the food bank manager to reschedule incoming and outgoing logistics activities.

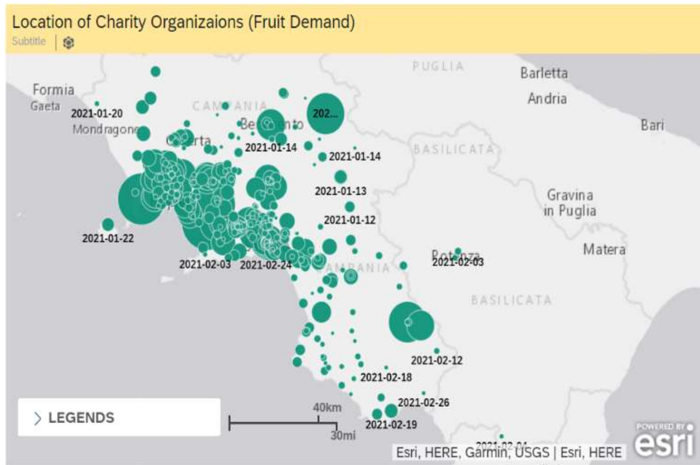

Figure IV.5 *Geo map of charity organizations based on their demand*

As shown in Figure IV.8, there is a big mismatch between incoming and outgoing logistics, which increases the risk of controlling the inventory level. A digital twin solution will be able to monitor disruptions and levels of perishable food inventory in real-time by synchronizing and predicting incoming donations and the amount of distribution. It's also possible to make sure that deviations from the plan are kept track of and that the logistical activities of getting fresh food from donors are rescheduled to meet the needs of charity organizations.

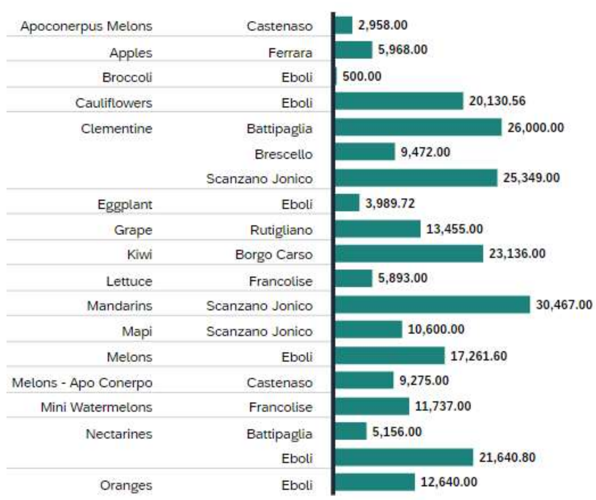

Figure IV.6 *Incoming fruit donations and locations of donors*

The model was created and trained in the SAP Analytics Cloud using historical data from the food bank. In the model, all the demand and supply quantities were expressed in kilograms. The experiment was done using annual data on irregular donations and distributions.

As shown in Figures IV.7, IV.8, and IV.9, after the automation of time-series data from the food bank database, the digital twin predicts both the number of incoming donations and demands by charity organizations. Based on the forecast, the food bank can reschedule and perform quick modifications to the inventory. More adjustments can be made to solve issues related to storage space. Due to energy consumption, the food bank has limited refrigerated room capacity to store fruits. There should be a balance between distribution and donations.

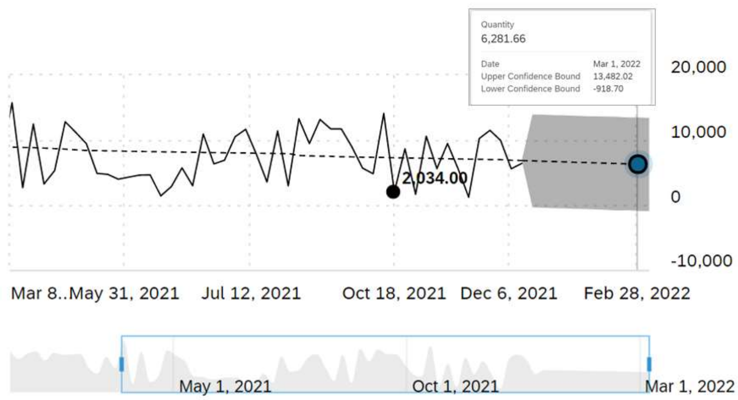

Figure IV.7 *Daily forecast of incoming donations*

Based on the traditional operation of the food bank, there is no way to have some insights to support the decision-making process. The analytics tool will enable the food bank to take a proactive approach. Otherwise, after one week of storage, the fruits will be discarded.

A digital twin, as proposed, can synchronize the supply chain network, improving collaboration between donors, food banks, and charity organizations. The information is collected and analyzed in near real-time for quick decisions. Since the fruits are highly demanded by a charity organization, the information can be used as input for the inventory replenishment process. Typically, donors provide fruits that have already begun to degrade in quality. As a result, fruits that arrive in food bank stores have an extremely short shelf life. Besides, based on incoming donations, the food bank will be able to initiate a quick delivery of fruits to charity organizations if storage space is not available.

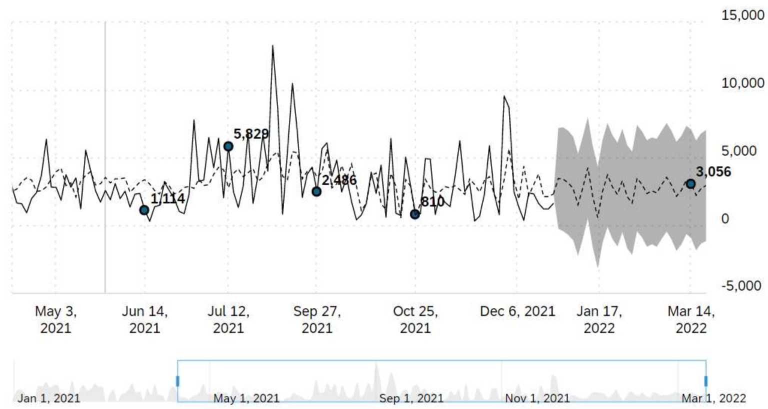

Figure IV.8 *Forecast for the demand of charity organizations*

Digital twins are living models that are constantly updated with current events. In line with this, the proposed approach will assist the food bank in predicting what needs to happen with its fresh food inventory and how other factors are influencing supply chain activities. The model is continuously updated with the most recent operational data to obtain real-time or near real-time data to feed into the digital twin.

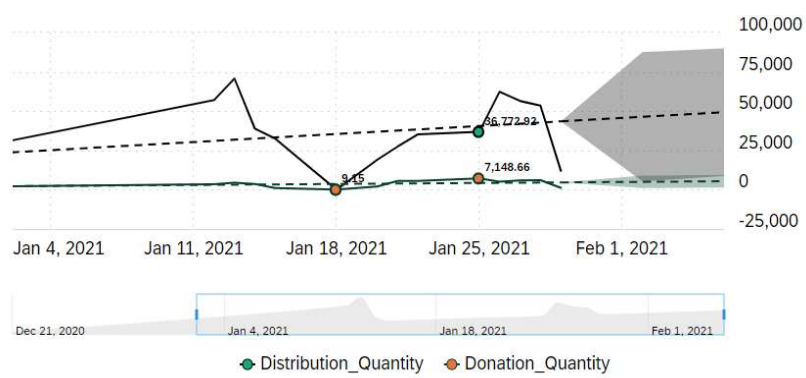

Figure IV.9 *Forecast on the amount of fruit donated and distributed*

The food bank can forecast the volume of donations as well as the demand for charity organizations using an automated time series. As illustrated in Figure IV.9, the quantity of demand by the charity is higher than the number of incoming donations. In this situation, storage space may not be an issue. As a result, the food bank can still receive more fruits. However, if the incoming donation exceeds the outbound logistics, the food bank will reschedule the immediate delivery of fruits to a charity organization, according to the predictive forecast.

Demand forecasting is critical for any firm. This involves having adequate inventory on hand to meet the demand of customers. A company that fails to estimate demand and orders insufficient inventory risks losing clients to the competition. A late order may cost more because supplier prices have risen in response to rising demand; this is yet another way the company loses money. If a company overestimates demand and orders too much inventory, there's a danger it'll end up with underutilized inventory and must pay for extra storage. If the company employs perishable inventory, it risks losing money on incomplete goods that have spoiled.

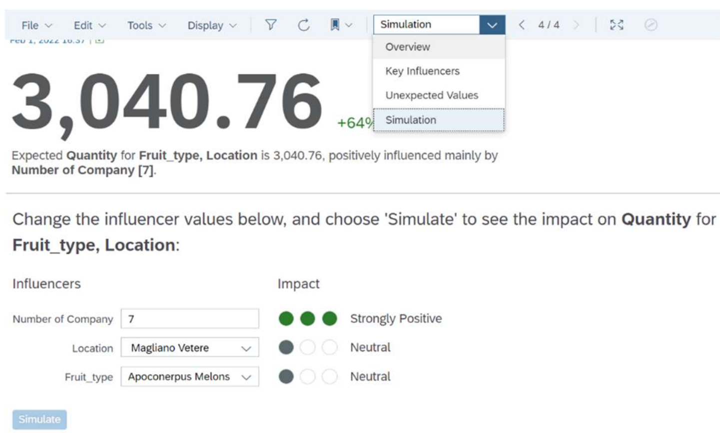

Figure IV.10 *Simulation to view the impact of key influencers*

Supply chain management is the process of matching supplies or inventory with customer demand. Because food banks are non-profit organizations, this logic does not entirely hold. Even so, they are unable to refuse to receive donations and orders from local charities that provide fruits to the needy. As a result, it might be best for groups like food banks to use digital twins to coordinate their activities and keep an eye on their inventory levels to change their plans.

In addition to prediction, using the simulation, it is possible to discover how changing the influencers has an impact on the value of demand quantity for fruit type and location by changing the values, the food bank can perform what-if scenarios (Figure IV.10). This will allow the food bank to design action plans to help them confront anomalous events, and evaluate those plans to verify they are effective.

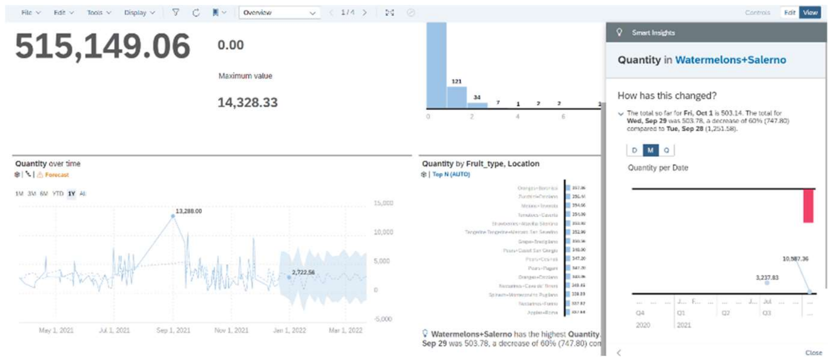

Figure IV.11 *Interactive storyboard for digital twin*

Overall insights into supply chain performance can be visualized through the storyboard as shown in Figure IV.11. Based on live data, the charts could visualize additional key influencers to understand the relationship between both key influencers and their impact on the quantity of fruit type and display predictive forecasts.

In general, the application of the digital twin can enhance collaboration and information transparency, which will allow for a more synchronized value chain with improved visibility and traceability. Food banks can begin to share data on inventory levels and demand forecasts with their primary donors and local charities to enhance the planning process, achieve faster inventories, and eliminate waste.

Chapter V
Digital twin integrated fresh fruit delivery

V.1 Introduction

The high perishability of fruits and vegetables is one of the characteristics that makes prospective surplus food particularly difficult to manage and val orize, posing unique logistical challenges. All parties in modern supply chains prioritize sustainability, and food waste issues receive major governmental, market, and media attention. Many companies have set up programs to combat it, and the food sector has also created programs with waste reduction as one of its primary goals. Perishable food items, in particular, must be transported with exceptional caution to reduce waste in the supply chain. Due to traffic congestion and fleet size constraints, it is difficult to ensure the extreme freshness of perishable products. Furthermore, the lack of cold chain facilities increases the risk significantly.

In logistics, it's not always easy to maximize fleet utilization. Fleet management software and tools arose quickly as a result of the internet. On the other hand, the digital twin supported by GPS tracking has proven to be the most useful tool for fleet management (Bosona *et al.*, 2013; Suraraksa and Shin, 2019). In line with this, controlling some of the metrics will help the stakeholders increase the vehicle utilization rate. Similarly, improved route planning through digital twin is another way to boost fleet utilization, with the ultimate goal of minimizing fruit waste during delivery. Due to route optimization, the vehicles will be on the most efficient routes entirely. This enables vehicles to arrive at their destinations on time or ahead of schedule. Moreover, route optimization reduces idle time and fuel consumption (Omar, 2008; Gracia, Velázquez-Martí and Estornell, 2014; Henke, Speranza and

Wäscher, 2015; Sassi, Cherif and Oulamara, 2015; Sourabh Kulkarni, 2016; Borčinová, 2017; Lin *et al.*, 2019; Liu, 2019).

The supply chain is among the most crucial aspects of logistics. It's a collection of organizations involved in several processes and activities, several of which are involved in many processes and activities. This network is linked to suppliers and customers, and its processes and activities produce value in the form of products and services for consumers. Every business creates a supply chain by combining the activities of the supply, production, and distribution zones.

Green transportation concerns are gaining interest from theoretical, political, and social viewpoints in today's highly competitive world (Adiba, Aahmed and Youssef, 2014). In the management of the provision of goods and services in distribution systems, routing issues are critical. The application of the optimization method, in particular, allows for significant cost savings (ranging from 5% to 20%) in worldwide transportation. With this subject, fleet management is inextricably related to any carrier's day-to-day operations. In many circumstances, proper fleet management results in a transportation company's or system's profitability (Zak, Redmer and Sawicki, 2011). The fleet size and mix problem becomes a mid-term planning issue when an organization plans to buy or lease a fleet of vehicles for future service. During the planning time, customer attributes like demands, time windows, and others are frequently related to uncertainty. A distribution plan should be developed, which includes the required fleet size, vehicle routing sequence, and the actual product that should be shipped out to allow for quality degradation during vehicle travel. For perishable commodities, several studies have been undertaken to determine an efficient truck routing policy and supply chain design (Hsu, Chen and Wu, 2013; Song and Ko, 2016; Vorkut *et al.*, 2019; Chan *et al.*, 2020; Pal and Kant, 2020).

Transportation planning using technologies, improved routes, and departure times may represent an economic opportunity to reduce food loss and waste. The usage of sensors and other IoT-enabled devices in the food and perishable commodities supply chain can improve product accuracy and delivery time. Intelligent algorithms have proven their worth and ability to solve difficult optimization problems in past few years. The majority of proposed solution strategies entail the implementation of heuristic algorithms to improve the likelihood of getting accurate results (Wang *et al.*, 2018). In the case of food recovery efforts, vehicle routing issues have received little attention (Mandal *et al.*, 2021).

One important option for the aggregator is to allocate donated food from stores to food banks to manage conflicting objectives such as maximizing business revenue while decreasing transportation costs, waste handling costs, carbon-equivalent pollution, and greenhouse gas emissions (Mandal *et al.*, 2021). Furthermore, because part of the food being transported is perishable, the products must be delivered at the proper temperature (Zhang and Chen, 2014). However, in our case, the vehicles do not have a fully controlled temperature system. Therefore, delivery optimization has become a top concern to reduce product loss resulting from long transit times.

Based on available data from the food bank, this study relies on the problem of determining the number of trucks required to provide a demand-responsive fruit delivery service. The approach aims to eliminate uncertainty during fruit delivery to charity organizations by optimizing the fleet size and vehicle route in near-real-time. The model's agents are made up of a network of local charity organizations, a single food bank, a fleet of delivery vehicles, and orders. The integrated GIS functionality is used to identify the agents in the model and to automatically determine routes based on the GIS provider's routes. The orders are created by the charities and then delivered to a food bank. These orders are represented by agents that communicate between the food bank and the charities. A process logic implemented in the production agent simulates loading the truck after receiving an order. After loading the trucks, the order is taken to the charity, unloaded, and returned to the food bank. Vehicle routes were also determined using the distance matrix (Table V.2). The goal of determining the most effective routes for trucks visiting charity stores was to find the ideal route. The optimum route is determined by the shortest distance that fits all of the parameters. Because fruits are perishable, shipping them over a short distance lowers the chance of product loss. Moreover, route planning allows an organization to make the most efficient use of resources and find the most cost-effective delivery routes, avoiding drivers' spending more time on the road and paying additional fuel and overhead costs. Furthermore, based on current inventory and fleet status, the planned output can be utilized to assess ahead of time if client demand can be satisfied (Hsiao *et al.*, 2018). The chapter intends to present digital-based fruit delivery based on data from food banks. Section 2 describes the problem, followed by Section 3 model implementation, and Section 4 results and discussion.

V.2 Problem description

The scope of this study was to create a simulation model for delivering fruit from a single distribution center to other customers. An optimization experiment is included in the model to determine the optimal number of vehicles for targeted utilization and the vehicle route. The model uses GIS functionality in AnyLogic software to locate the agents and determine routes. AnyLogic is a handy piece of software for simulating complicated systems since it accurately depicts real-world phenomena. With the addition of GIS maps, it offers a wide range of uses (Li, Zheng and Cao, 2011). Through its broad library, AnyLogic simulation software provides an excellent technique for modeling networks. System dynamics, agent-based modeling, and discrete event simulation (DES) are among the simulation approaches supported. AnyLogic allows users to mix and match components created using agent-based or discrete event approaches with system dynamics model components.

Various agents are employed, including distribution centers, organizations, trucks, and orders. The organization creates orders, which are then received by the distribution center. The distribution center will begin loading the truck once the orders have been received, followed by delivery of the order to the requesting organizations, unloading, and returning to the fruit distribution center (food bank).

VRP is a combinatorial optimization and integer programming problem that involves determining the best set of routes for a fleet of vehicles to take to deliver goods to a set of consumers. The fact is that products are being delivered from a central depot to clients who have made orders for items. The VRP's goal is to reduce the entire route cost as much as possible.

Vehicle routes were determined using a GIS distance matrix. This optimization task's purpose was to determine the most efficient routes for trucks visiting a certain group of clients. The shortest distance that fits all of the parameters determines the best route. Fruits are perishable, thus shipping them over a short distance reduces the risk of product loss. Combinatorial optimization was also used, which seeks to discover the optimal solution to a problem among a huge number of options. The Python programming language was used to test the model's performance using OR-Tools which is an open-source optimization software suite for solving vehicle routing. The capacitated vehicle routing problem (CVRP) has been implemented with various assumptions. Because the cars have limited space, all of the fruits should be sent to distinct locations.

Python's versatility and usability have contributed to its explosive growth in popularity during the past decade. The Pypeline (a python connector) package, which enables communication with any locally available Python version, can connect it to AnyLogic. Python optimization model can be run using a Pypeline. A Pypeline is a special-purpose AnyLogic library that allows users to call Python within a running model. It establishes a connection to a local Python installation, allowing users to use any Python library (AnyLogic, 2020).

V.3 Model implementation

V.3.1 Model framework

The AnyLogic software was used to model the supply chain network for fruit delivery to 350 charity organizations (Figure V.1). However, for simplicity purposes, we have considered only 6 main charity stores where small charities collect the fruits (Figure V.5). Initially, the software's GIS capabilities were used to determine the locations of organizations and distribution centers where the digital twin solution was implemented. The logic has been built with the processing of an order, loading, and unloading of the truck, and the return of the truck to a depot to enable the process of order communication between the distribution center and customers. The target utilization for optimizing vehicle size was set at 85 percent, meaning that the remaining utilization was considered downtime due to maintenance and related issues.

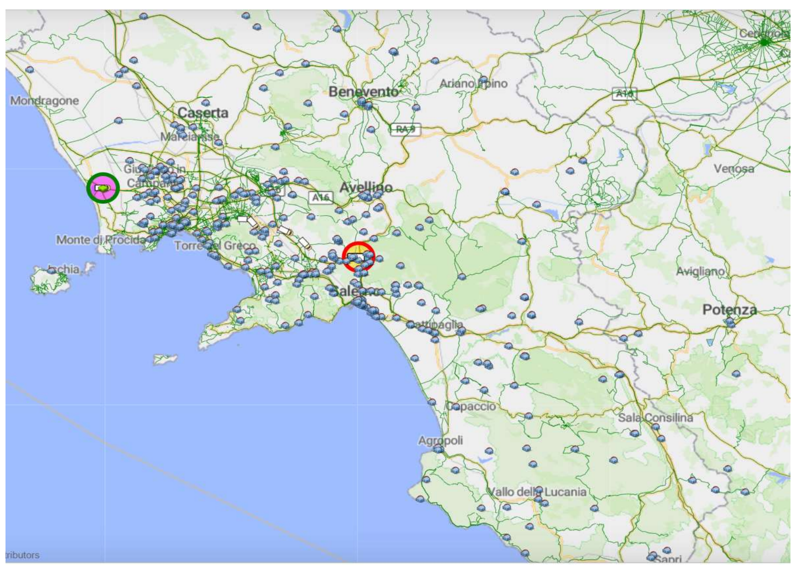

Figure V.1 *Agent locations on the GIS map*

The fruit delivery model was developed based on data from the Italian food bank. GIS data and current customer demands, including those of charity organizations, were used to model the process. The GIS network has been used to use the existing roads and avoid some approximations in the model. The shortest route was requested from an open street map during this modeling (OSM server). The model is designed to reflect the typical scenarios of donors, charity organizations, and food banks serving low-income communities. The model relies on a single distribution center and a fleet of six vehicles to supply items to local charities that are supposed to collect items from nearby six main charity stores. Because the distribution center owns these trucks, it was chosen as the starting point.

The donors send the fruit items to the food bank using their fleet. The food bank distributes fruits to small charity organizations based on their demand. In the same way, the food bank uses its vehicles to deliver fruit to charity stores in the area.

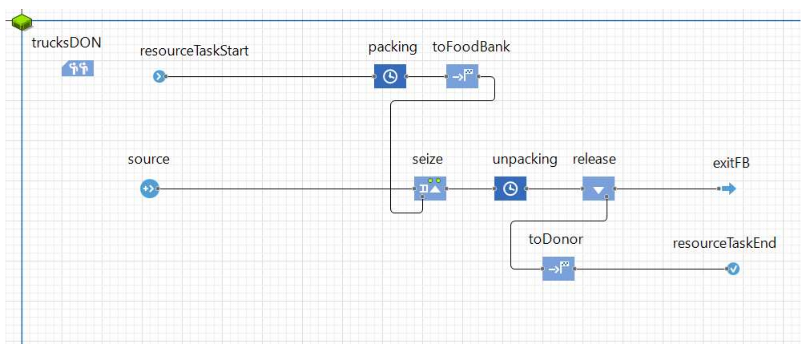

Figure V.2 *Supply chain operation of donors*

In process modeling (Figure V.2), the "entry" block receives orders and is connected to the "seize" block, which captures resources. Before receiving the resources, the packing process takes place to prepare goods. The vehicle will deliver and return to the process step defined in the "resourceTaskStart" and "resourceEnd" processes at the same time. The packing process was modeled using a delay block that represented the delay of agents for a specified period uniformly distributed between 1 and 2 hours. After the fruit has been loaded, it will be distributed to the clients who have been designated agents. The truck will be unpacked after a delay of 1 to 2 hours when it arrives at the organization.

When fruits are available in the food bank inventory, orders from charity arrive, and a request for logistics service is issued in the seize block (Figure V.3). This is the information used to create "resourceTaskStart". The fruit is then packaged and loaded onto the truck before being delivered to the charity. The order and the truck agent are combined in the seize block. When the products arrive at the charity, the process of unpacking begins, and the orders are freed, destroying the combination through the seize block. The truck then returns to the food bank to await the next order. The order is returned to the charitable organizations. When the inventory is empty, however, an order is sent to the donors, and when the requested items become available, they are brought and added to the food bank inventory.

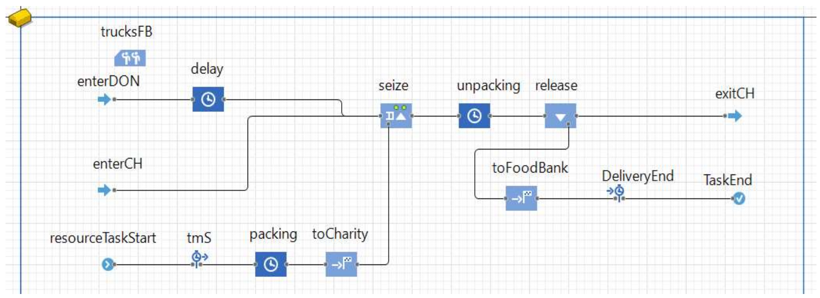

Figure V.3 *Supply chain operation of food bank*

The model for charities starts with the source "order" and moves to "sink" after it is fulfilled. Because there are 6 distinct charity stores, the information in the exit block designated "exitFB" should first be stored to identify where this order came from (Figure V.4).

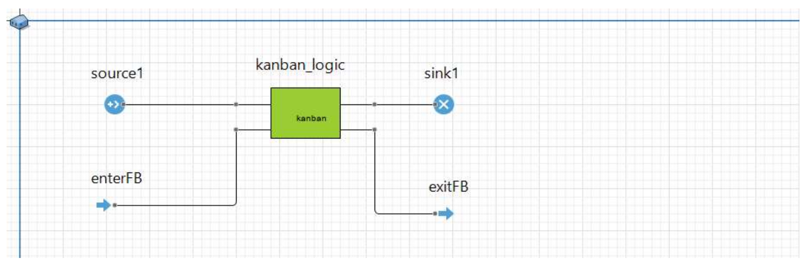

Figure V.4 *Process modeling logic for the agent of the distribution center*

V.3.2 Optimization of fleet size

The strategy was first tested with 12 donor trucks and 8 food bank trucks, yielding an asset utilization rate of 65%. An optimization experiment was then carried out to determine the best configuration of an optimal number of trucks that could be used for delivery services from a single depot. The model was able to determine the optimal fleet size by ensuring that the average utilization was at least 85 percent. The boundary was set between 1 and 15, and the truck number parameter was set to “discrete”.

Figure V.5 shows the Service map of the main charity stores that are used in the capacitated vehicle routing. The places indicated in number are locations of main stores of charity organizations where other small charities clustered based on their distance are used to collect fruits for their customers.

Figure V.5 *Service map of the main charity stores*

V.3.3 Capacitated vehicle routing

A VRP in which vehicles with limited carrying capacity must pick up or deliver products at numerous places is known as the CVRP. The items have a quantity, such as the weight or volume, while the vehicles have a carrying capacity. The objective is to pick up or deliver the products for the least amount of money while never exceeding the vehicles' capacity. Six main charity places were established to provide the fruit items depending on specific demands to address this problem. In the model, fresh produce is transported from a single depot (food bank) to charity stores serving small charities in a cluster using a range of vehicles with varied capacities.

V.4 Results and discussion

V.4.1 Fleet size optimization experiment

A fixed number of vehicles was considered in the optimization experiment for fruit delivery from donors to the food bank. The experiment was primarily concerned with maximizing truck utilization of fruit delivery from the food bank to charities at a given time. At the time of optimization, two trucks account for 84.5% of the fleet's utilization. After the experiment was over, the model was tested with the right number of trucks in it.

Initially, the fleet utilization was 39% when using 6 trucks, but after optimization based on real-time demand requirements from charity organizations, the utilization has improved significantly (Figure V.6). In this case, using a digital twin can not only reduce food waste but also cut down on emissions, provide real-time updates and insights, improve vehicle maintenance, and improve overall logistics performance.

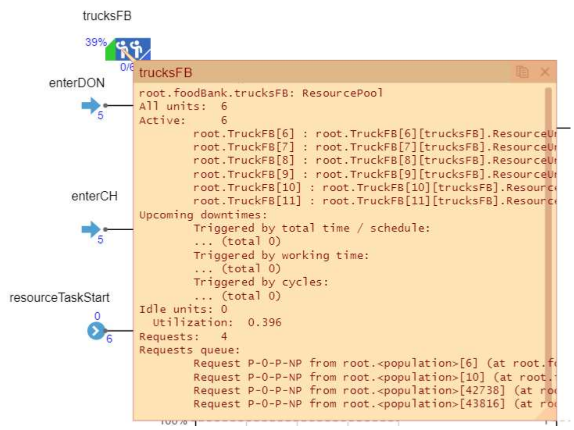

Figure V.6 *Fleet utilization before optimization*

To develop effective vehicle routes, a heuristic approach was utilized to increase total customer satisfaction, which is based on the freshness of distributed fresh produce.

Figure V.7 *Screenshot of fleet optimization*

V.4.2 Optimization of vehicle route

It is presumed that each customer's location, as well as the number of ordered fruit goods, as well as the number of ordered fruit goods, are known. Furthermore, the capacity and number of vehicles available are predetermined.

The distance matrix is an array whose i, j entry represents the distance in kilometers between locations I and j, with the array indices corresponding to the following locations: 0, 1, 2, 3, 4, 5, and 6. Different demands are placed on the order of the places in the distance matrix. Because this is a capacitated vehicle route, there are five vehicles from the food bank in the problem, each with a different carrying capacity. The depot serves as both the starting and ending point of the route. The depot is 0, in this case, which corresponds to the location of the food bank.

Table V.1 *Distance matrix of main stores charity organizations*

	Depot	City1	City 2	City 3	City 4	City 5	City 6
Depot	0	12.3	112	27.8	58.8	61.5	68.5
City 1	12.3	0	105	40.1	57.3	73.8	80.5
City 2	112	105	0	135	67.4	149	179
City 3	27.8	40.1	137	0	52	47	64
City 4	58.8	57.3	166	52.3	0	92.4	33.7
City 5	61.5	83.2	134	54.7	99.7	0	83.8
City 6	68.5	179	109	64	33.7	57.8	0

Customers will be able to acquire more fresh food items, and the food bank will be able to attain a higher degree of customer satisfaction in this instance. Refrigerated automobiles, on the other hand, are more expensive and consume more fuel than non-refrigerated vehicles. Due to the economic situation, it is difficult to operate refrigerated-type vehicles for every delivery. General-purpose vehicles for perishable food product delivery may be ideal in this instance. As a result, adopting a digital twin-based near-real-time vehicle route optimization would be the best solution for non-profit organizations like food banks.

The output for each location on a route provides the location's index and the total load carried by the vehicle as it leaves the location (Tabel V.2). If the overall quantity of fruit items being transported does not exceed the total capacity of the vehicles, a routing problem with constraints has a possible solution in CVRP. If not, the solver may run a time-consuming exhaustive search.

Table V.2 *Output of capacitated vehicles routing problem*

	Vehicle 1	Vehicle 2	Vehicle 3	Vehicle 4	Vehicle 5
Vehicle route	0-2-0	0-6-5-0	0-4-0	0-3-0	0-1-0
Distance of the route (km)	224	186	116	541	24
Load of the route (kg)	1280	1440	1440	1040	1510

Transportation has a high rate of negative impacts on the environment, such as pollutant emissions (greenhouse gases). The loss of the ozone layer and climate change are the immediate consequences of these impacts. As a result, companies must continue to cut emissions from the industry by reducing the delivery frequency and maximizing truck capacity utilization. CVRP, which aims to cut down on greenhouse gas emissions, especially carbon dioxide, has problems figuring out how to get vehicles to serve a group of customers while also cutting down on gas emissions and the loss of perishable goods.

Chapter VI
The framework of a digital twin implementation in the fruit supply chain: based on food bank operations

VI.1 Introduction

Obtaining a detailed real-time snapshot of the supply chain network in practice is challenging. The advent of the digital twin, on the other hand, has made it possible to solve this problem. The entire concept tends to revolve around developing a virtual and digital counterpart to the physical system based on enterprise data to exploit the effects of different parameters and make more informed decisions (Dehghanimohammadabadi, 2022).

Organizations can benefit from new approaches to supply chain management that utilize cutting-edge technological and analytical methods while also producing new revenue streams and increasing overall business value by implementing a supply chain digital twin. As compared to implementation in manufacturing or a piece of machinery, a supply chain digital twin requires the modeling of the entire supply chain supported by real-time or near-real-time operational parameters (Ivanov and Dolgui, 2021). Inventory, product logistics, online shelf placement, the entire online management of incoming and outgoing products, and electronic tracking and automated planning of all materials are the main processes of the digital supply chain.

The usage of industry 4.0 tools like digital twins, which is a virtual representation of a product, such as fresh horticultural produce or a system, is now beginning to improve collaboration in agri-food supply chains. Environmental sensors allow a virtual product to communicate with its physical counterpart. In food supply chain networks, statistical and data-driven (intelligent) twins can measure the quality loss of fresh horticultural produce by recognizing patterns in the data and using physics-based and machine-learning models to better understand the physical, biochemical, microbiological, and physiological processes (Defraeye *et al.*, 2021).

The use of IoT and digital twins to improve shelf life and reduce food loss has gained significant popularity. It has been reported that IoT is being used in agricultural production sectors such as controlled environment agriculture, open-field agriculture, and livestock applications (Neethirajan and Kemp, 2021; Verdouw *et al.*, 2021). In recent times, the use of IoT for tracking goods, traceability, and monitoring the environmental conditions, weight loss, and overall quality loss in the postharvest supply chain has also caught the interest of the food industry (Jedermann *et al.*, 2014; Zou *et al.*, 2014). This method has also received considerable attention in the development of intelligent packaging in the food industry (Ghoshal, 2018). Sensors and indicators (time-temperature indicators, freshness indicators, gas indicators, and integrity indicators) are used in smart packaging to detect biological, chemical, or gaseous changes in packaged fresh produce (Pal and Kant, 2020). Sensor-based RFID tags can detect corresponding attributes and chemical changes in fresh fruits and vegetables throughout the post-harvest supply chain (Zou *et al.*, 2014). The package system's quick and efficient data collection can be used to notify decision-makers in the supply chain of an event that may cause serious damage to the packaging or the fresh produce itself. Another approach used to check the real-time state of fruits throughout the post-harvest period is thermography (Manickavasagan and White, 2005; Leizi, 2017; Gurupatham, Fahad and Hudlow, 2018; Feng, Zeng and He, 2019; Ferreira, 2020).

Overall, the use of IoT in various cold chain operations generates a large amount of real-time data, which can be used to build and maintain the foundation for new machine learning techniques such as artificial intelligence and big data analytics (Pang *et al.*, 2015). Even though IoT-based applications like the digital twin are important to control cold chain technologies to reduce food losses in the supply chain of fruits and vegetables, their implementation is still in its early stages. Moreover, this technology would help multiple supply chain partners control and optimize their systems for better decision-making.

This chapter intends to develop a digital twin framework for agri-food, specifically for food banks, by combining machine learning techniques, agent-based models, and data-driven approaches. The idea aims to integrate highly innovative technological paradigms (digital twins) into the pipeline of the fruit supply chain. It proposes a transition compatible with the strength of the field actors, who can voluntarily and gradually adopt the new working framework (platform and methodology), which will be compatible with other methods of managing food recovery. Food banks will be used as a reference model in the framework. These are nonprofit institutions that collect and distribute food. This chapter includes three sections. The digital twin-based decision support system for the agri-food supply chain is described in Section 2. Section 3 covers the proposed framework for a digital twin that integrates a fruit quality monitoring system (product twin), a data-driven time series-based approach, and a delivery model.

VI.2 Digital twin-based decision support system in agri-food supply chain

Supply chain coordination is essential for the success of stakeholders involved in the supply chain network. This section describes the details of an integrated solution from donors, food bank, and small charity organizations that provide fresh fruits to end-users (Figure VI.1). This approach is expected to simplify the complex relationships between food banks, donors, and charities if properly integrated.

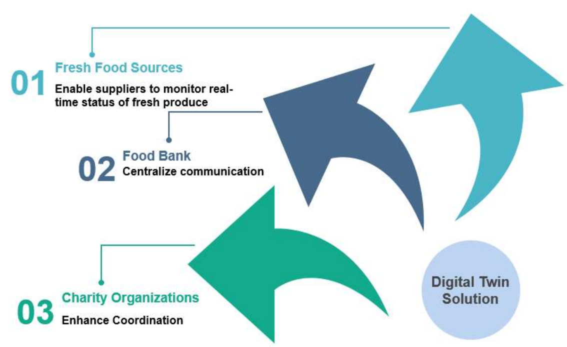

Figure VI.1 *The pillars of the proposed solution*

The proposed solution enables food banks to manage their charity networks by connecting with relevant allies based on the digital twin solution as an umbrella layer. Empowering food banks with digital twin applications is the key to improving coordination along the food supply chain that could deliver fresh produce to end-users. Furthermore, developing waste-reduction solutions across the fruit supply chain is crucial for suppliers since it lowers waste disposal costs while simultaneously improving the lives of the poor by distributing free food through charity networks.

Fresh food suppliers (donors in our case) lack good visibility to monitor the real-time status of fresh food in stock and end up wasting massive amounts of food. Although it is possible to donate these foods before they deteriorate completely, the likelihood of using fresh foods for animal feeding and landfill is still high. In a world where a growing number of people live in relative poverty, this is not the best way to manage food waste. Furthermore, because fresh foods like fruits are highly perishable, improving coordination and speed of delivery with an adequate quantity is required to improve the effectiveness of charity organizations and to assist end-users in reducing hunger and poverty.

This problem can even be solved with limited resources by collaborating with retailers and charities working in cities with high poverty rates and high fruit and vegetable waste (Figure VI.2). Apart from the enormous volume of waste, food banks and local charities are unable to establish a logistical collaboration that would eliminate disruptions and uncertainties associated with the availability and delivery of perishable foods.

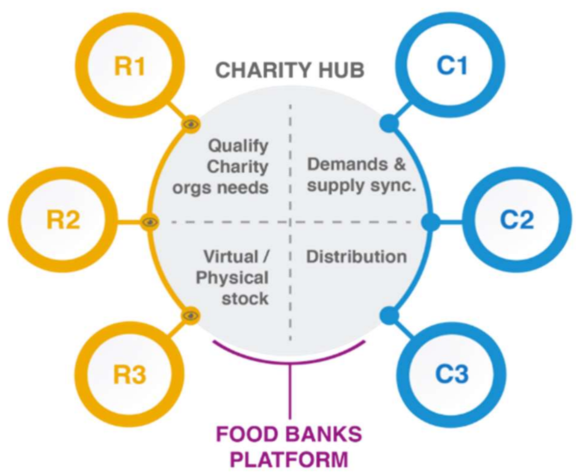

Figure VI.2 *Value proposition based on retailers, food banks, and charity interactions*

This work provided a solution that consists of three complementary components, as shown in Figure VI.5. The first component is a digital twin for tracking product quality evolution (product twin), which enables suppliers' real-time visibility into fresh food reaching expiration dates. The second part deals with inventory control, followed by a collaborative logistics platform (called a "delivery model" of the supply chain).

Instead of just providing a number, visualization of the decision support process offers the foundation for a shared understanding of the problem space, which in turn facilitates value co-creation between supply chain stakeholders with varied views. In the case of the digital twin, this is accomplished by the integration and use of the relevant shared data.

VI.3 Proposed framework

A supply chain digital twin is a complex simulation model of an actual supply chain that anticipates supply chain dynamics using real-time data and snapshots. Analysts can use this information to better understand the behavior of a supply chain, predict unforeseen events, and devise a plan. It benefits the organization in a variety of ways, including increasing collaboration and providing a more robust decision-making process within the framework of the supply chain.

Simulation in supply chain operations can be performed either offline or online. Offline in this context means that the simulation is detached from the real system and relies on the user to update parameters and data to maintain the model's accuracy. Online simulations, on the other hand, where the model is directly connected to the real system and is automatically updated as the system changes, are usually referred to as a "digital twin" (Chaplin, Martinez-arellano and Mazzoleni, no date).

Our framework comprises supply chain activities from the real-time product (fruit) monitoring to delivery optimization. Customers' orders are regarded as the starting point for the supply chain's cycle of activities, and managing the orders through an integrated data warehouse improves the overall process's visibility and transparency. Traditional integration systems have limitations, such as the inability to respond to dynamically changing orders, supply chain disruptions, and a lack of real-time inventory visibility. This type of system is also subject to security concerns and lacks decision-making capabilities supported by simulation, prediction, optimization, and data analytics. Because of their ability to gather insights on ongoing operations, such as order and delivery status, digital twins have been thought to be an excellent solution for monitoring and controlling supply chain activities. AI and machine learning techniques are used in the tool, and real-time data from the physical system can be acquired via sensors to evaluate and disclose faults in the supply chain network.

This study posits an IoT-based food supply with dynamic truck routing to ensure both food quality freshness and the quickest delivery attainable. Multiple sensors detect and monitor food quality, safety, and freshness at each level of the food supply chain in the IoT-based food supply chain. These sensors send data to the control and monitoring system, which collects, consolidates, and records the information in a database before sending it to contamination tracing modules at cloud computation.

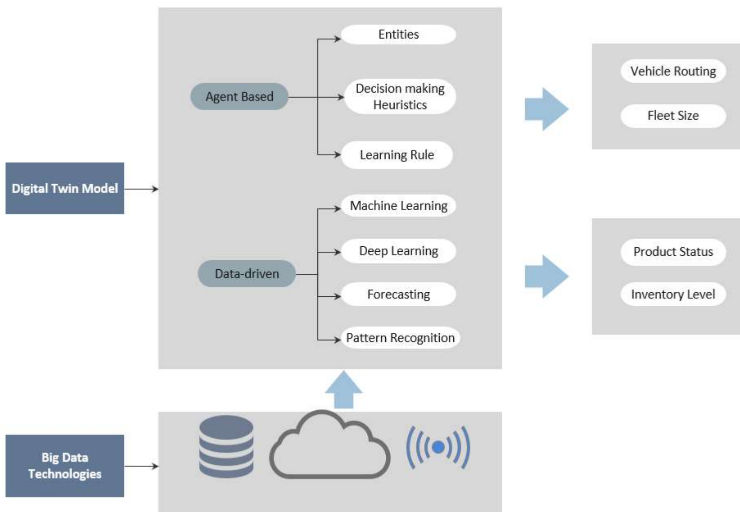

Figure VI.3 *General solution architecture*

A supply chain digital twin can obtain data by integrating with business applications such as manufacturing integration systems, ERP software, and supply chain-specific tools. In our specific proposal (Figure VI.3), we use the food bank database for inventory and delivery optimization and the data from the thermal cameras to capture real-time physiological changes in the fruit.

This framework uses three supply chain points that are to be held responsible for fruit losses. This includes the suppliers (in our case, donors), the food bank inventory, and the delivery process. The virtual model in the proposed framework contains all of the necessary elements, including the product's internal and external defects, inventory level, and fleet and route optimization. Digital twins can be physical, statistical (empirical), or intelligent (using machine learning and deep learning) (Defraeye *et al.*, 2019). This framework, however, will rely on machine learning and the use of analytics tools. It has also considered a delivery model that can be updated in near-real-time with data from the food bank database, intending to optimize fleet size and vehicle route.

Fruit suppliers waste too much time and energy identifying and removing spoiled fruits and vegetables manually. Automating the recognition system through the digital twin could solve the problem by triggering information for operators. Through SAP intelligence services, the virtual copy of the product provides up-to-date information about the product's status, allowing the user to intervene before waste occurs. Furthermore, using the SAP Cloud Business Suite, all partners in the fruit supply chain network could centralize communication and increase coordination (Figure VI.4).

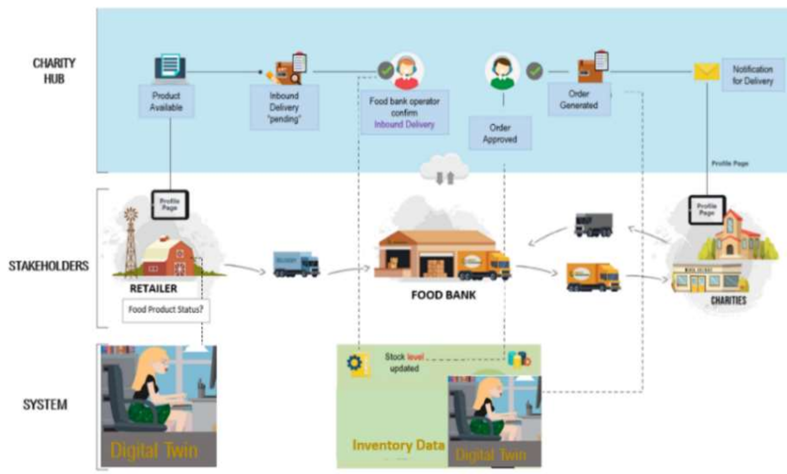

Figure VI.4 *Integrated digital twin-based solution for fruit monitoring and delivery*

In the above framework, the status of food items will be monitored using the digital twin, and predictions and feedback will be sent to the operators. This will allow the operators to estimate how much food should be donated to food banks before the loss. The stakeholders will communicate via the digital twin-enabled platform while the fresh produce is constantly tracked. The system could support the whole communication capability, reducing the likelihood of uncertainties. Moreover, food redistribution and sharing are ubiquitous in communities, but how individuals share and redistribute food is changing. By utilizing adequate information and communication architecture, digital twins can enable two or more counterparts to communicate in a network without the need for central coordination. It can promote food sharing and redistribution via web platforms or apps, which leads to continuous visibility, which demands timely and integrative communication and marketing strategies to support the model of food banks' viability. Donors, food bank, and local charities can work together to assist companies by contributing their products and feeding people with little effort.

Figure VI.5 depicts a potential configuration for developing a digital twin of the fruit supply chain using real-time or near-real-time data. Vehicle routing, inventory planning, and product status monitoring can all be used in optimization through a digital twin. For product twin and time-series-based digital twin development, SAP intelligent services can be used, and AnyLogic software will be used for delivery optimization. When fully integrated, the digital twin will provide insights based on both thermal and supply chain historical data. In addition, delivery optimization will take into account the number of trucks and route data.

The digital twin will send out notifications depending on the status of the fruit, which could be beneficial to end-users. Donating the fruit, dumping it from inventory, or offering discounts based on the degree of defect are all options. In addition, based on the forecast, the food bank will be able to decide whether to accept or reject incoming orders. The solution will also assist in determining the fleet size and the best route for delivering fruit to local charity organizations.

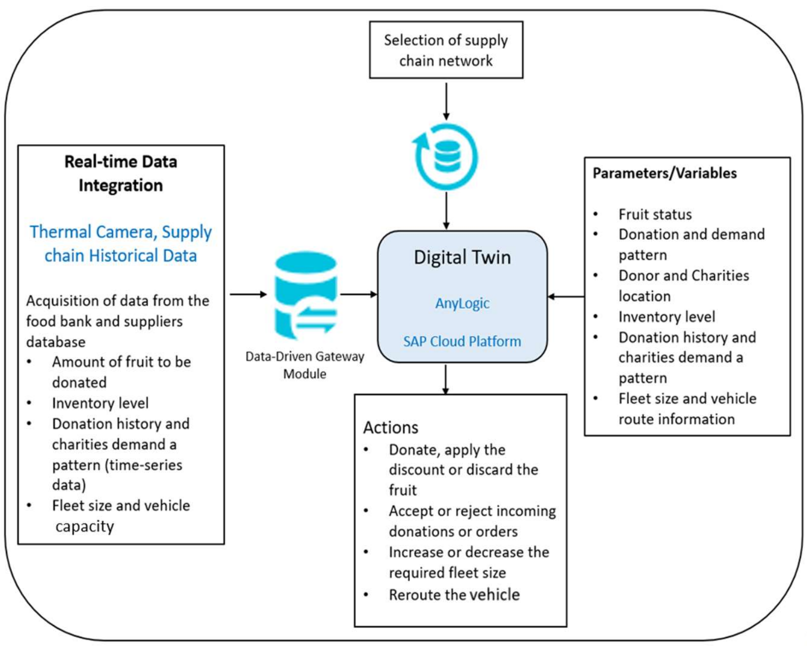

Figure VI.5 *General proposed framework for fruit supply chain digital twin*

The development of a digital twin requires IoT-based devices that capture the operational behaviors of resources and processes, as well as their functional properties. Communication infrastructure provides reliable and secure data delivery from physical devices to the digital space. As a modern database server, a digital platform that integrates supply chain data with high-level business data using advanced machine learning techniques, actionable insights are extracted from different data sources for data-driven decision-making. The maturity and availability of the IT infrastructure determine how complex and detailed the digital twin models are.

Food banks are using SAP tools that can be integrated with the cloud platform. Because SAP enables cloud storage and data can be easily kept, we chose SAP tools and AnyLogic software in the proposed solution. Because AnyLogic has its cloud storage, data can be transferred from the SAP cloud to the AnyLogic Cloud (Adhikari *et al.*, 2021). The simulation model can be developed using data from AnyLogic cloud computing and the AnyLogic simulation database to implement the digital twin. AnyLogic's simulation database can link to other databases. The AnyLogic simulation model can be used in SAP CRM and BI, as well as SAP ERP and MES.

Conclusions and industrial implications

In this research, the applications of digital twins in common industrial processes and the agri-food supply chain were analyzed. Moreover, methods have been developed for the fruit supply chain that could reduce waste. A set of goals has been established for this project. First, the study conducted a systematic literature review on the industrial use of digital twins in commonly used domains such as production, predictive maintenance, after-sales services, and supply chain, followed by an analysis of recent advancements in the agri-food supply chain. Moreover, this work has focused on creating a digital twin based on machine learning that would allow the food supply chain to track the status of fruits in real-time throughout storage. The study has also presented an automated time-series-based digital twin that will allow us to optimize food bank inventory depending on the demands of local charities and donors. After the case studies for digital twin implementation, the project has focused on optimizing the fruit delivery system for local charities. The solution has also included a general framework of digital twins based on a model of Italian food bank operations.

The literature review examines the current state of the art in the definition, concept, types, application tools, and maturity framework of digital twins. In addition, the study looked into the application and economic prospective challenges of using digital twin solutions. One of the important contributions of the review is to assess recently published studies and comprehend the most recent use of digital twins in key operational phases and the supply chain. The analysis found shortcomings in the deployment of digital twins in the food supply chain, particularly for the management of fresh produce, which results in the loss of large volumes of fruit that are still safe for human consumption. The use of digital twins is emerging as one of the viable methods for improving the management of perishable food items by increasing visibility. Researchers in the sector have outlined promising ideas, but the problem of data acquisition has made it difficult to use digital twins in the perishable food supply chain. A research-intensive literature survey was conducted to determine the optimum data gathering tool for capturing the real-time state of fresh produce, and a machine learning-based methodology was adopted, using thermal cameras as a data source to develop a digital twin of the fruit. Real-time product tracking will reduce waste throughout the supply chain network. Furthermore, the study established an automated time series-based digital twin to monitor inventory level, which is identified as the second supply chain point responsible for significant fresh product loss. Besides, the solution includes a framework for optimizing fruit supply to local charity organizations in near real-time. Finally, the basic architecture encompasses fruit quality monitoring systems, inventory planning models, and delivery models that all work together to keep fresh food from going to waste in the digital twin-based agri-food supply chain. This study is expected to add additional value to the fruit supply chain while improving coordination among stakeholders in the fruit supply chain network.

In this research, the first suggestion I would make to the entire agri-food business is to increase the level of readiness to use digital twin technologies. Previous research into digital twin applications in the food supply chain has remained hypothetical. As a result, the sector should focus on expanding the technological infrastructure that supports the implementation of a digital twin. Also, the missing knowledge of employees, the size of the system, and many legal rules must be taken into account. Furthermore, food items are complex, and collecting the real-time status of products, particularly perishable fresh produce, remains difficult. More study is required to create and use sensors capable of capturing real-time data from fresh produce. Furthermore, cloud-based services should allow data exchange across stakeholders in the supply chain network so that all parties can conveniently access data that can be used as input to a digital twin application.

The implementation of a digital twin requires data integration. In this study, data ingestion was performed manually, and more research is needed to integrate the required components to build a fully functional and automated digital twin. Furthermore, the study uses banana fruit in the development of the product twin, and the approach should be validated with other fruit types as well. In addition, for practical implementation, the food bank database should be able to be synchronized with SAP Analytics Cloud and AnyLogic software.

Due to a lack of adequate real-time data and a time constraint, the static simulation model was used in this study; nevertheless, we are still working to create a fictitious database to build a virtual environment of a supply chain network. The key limitation of this study is gaining access to critical data from SAP and AnyLogic, as well as real-time data from the fruit supply chain, to assess digital twins. Machine learning methods can be used to add real-time data into the AnyLogic aggregated simulation to complete the virtual world of a digital twin for further research. It's also worth looking at data exchange with integrity from the SAP Cloud to the AnyLogic Cloud.

The results of this study can help stakeholders and policymakers improve fruit waste management throughout the fruit supply chain. Supply chain optimization enables fruit supply chain operators to adopt a proactive approach to lowering overall costs while also improving the social impact and other sustainability goals.

Major players in the fruit supply chain are currently facing disruptions and obstacles from a variety of causes, including product loss, logistical challenges, limited resources, uncertainty, and growing customer demand. The digitalization of the supply chain connects all partners to produce a more effective and seamless workflow. Thus, a supply chain digital twin can improve visibility and efficiency in operations. Although they realize the need to invest more in technological transformation, fruit supply chain partners are far from ready to benefit from digital twins. Otherwise, firms in the fruit supply chain are likely to lag behind and eventually go out of business. The proposed approaches can be used to execute fruit monitoring operations, reducing the variety of issues that manual sorters must deal with. Moreover, the thermal camera's high capability allows the fruit status to be easily acquired as infrared images of fruits, which are then quickly analyzed, and quality attributes determined. Depending on the conditions, stakeholders can take proper actions to prevent the item from being lost. High-quality products will attract a premium price from retail customers. To meet these requirements, products should be devoid of defects, and their status should be monitored in real-time. Similarly, having the potential to automate fruit quality monitoring utilizing the envisioned digital twin idea will assist enterprises by lowering waste and operational time. Furthermore, the proposed approaches could improve supply chain forecasting and allow for improved fresh produce inventory planning for retail warehouses, suppliers, and non-profit organizations that are dealing with fruit waste due to demand-supply mismatches. These industries may utilize digital twins to access enormous amounts of data and analyze it in near real-time to precisely forecast future demand or supply chain changes. Besides this, companies must continue to reduce emissions from the fruit logistics process by reducing the delivery frequency and maximizing truck capacity utilization through the adoption of the envisaged digital twin.

Implementing our study output can help stakeholders in the fruit supply chain improve end-to-end visibility. This research makes a significant contribution to operational transparency and the creation of trustworthy relationships with fruit supply chain partners.

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