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SURVEY

Machine Vision and Robotics for Primary Food Manipulation and Packaging: A Survey

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ABSTRACT Vision and Robotic technologies are progressively becoming ubiquitous for automating and digitizing quality control in the food industry. This paper aspires to provide a high-level technical review on the crucial role of advanced automation technologies, including versatile or dedicated robotic systems, specialized end-effectors, machine vision, and efficient material handling systems, which collectively enhance food processing efficiency. While the manuscript aims to document the various automation sub-systems utilized generally in food processing, it places a particular emphasis on the primary processing phase of food production. Most food products in the primary processing phase exhibit a plethora of complex physical properties and manipulation conditions, making it difficult to reliably automate the various processes. This research aims to outline the contemporary advances and requirements for integrating various automation technologies, to enhance the efficiency and precision of primary food processing. Furthermore, it aspires to serve as a valuable, up-to-date survey and analysis of the latest advances in automation and vision technologies and their capability to automate a food processing line.

INDEX TERMS Artificial intelligence, conveyors, end-effectors, machine vision, primary food processing, robotic systems.

I. INTRODUCTION

Global food production and processing is capable of sustaining today's human population, which has recently surpassed the 8 billion mark [1]. It is estimated to reach 9.7 billion in the mid 2050's, and peak at around 10.4 billion in the 2080's [2]. The global consumer spending on food which was totalling approximately \$7457 billion in 2019, is expected to grow at a rate of 7% to \$11,167 billion by 2025 [3]. These indicators point towards the rise in demand on a global scale for food production and related processes.

According to the FoodDrinkEurope (trade association which represents Europe's food and drink industry) Data & Trends 2023 report, the industry employs 4.6 million people, generating a turnover of €1.1 trillion with €229 billion in value added [4]. However, the median wage for personnel in the food service sector is notably lower at €14,600 [5] compared to the EU average of €30500 [6] across all industries. <Additionally, the food service sector has the lowest rate of job automation at 24% [7], indicating that a large volume of production processes are performed manually, involving low-skilled and part-time workers. Concurrently, the EU is the largest exporter of agri-food products with a revenue of €182 billion in 2023 [4], and this statistic is projected to rise in the coming decades, with the growing global population and increasing purchasing power of people from developing nations [8].

Prior to the industrial revolution, the majority of industries relied on manual equipment and processes to produce and process food. However, the rapidly growing global population, coupled with declining regional (European) populations and increasing quantity of global food consumption, has

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become a primary driver for the food industry to innovate and upgrade its production processes, by automating the entire production or at least certain individual sub-processes. More notably in the European context, the food and agribusiness industry which was traditionally low-tech, is increasingly implementing robotics and special automation machinery, to offset workforce issues and to increase output yields while reducing waste [9]. This shift towards automation is also accompanied by a gradual increase in R&D expenditure, with small and medium-sized enterprises (SME) prioritizing product and process innovation, reflecting the sector's response to evolving market demands and technological advancements [10].

Large scale food processing units usually have the resources and a market stable product, enabling them to get dedicated Special Purpose Machinery (SPM) to profitably automate their production lines. On the contrary small and medium enterprises (SMEs), which comprise of 99% of the entire food industry in Europe [11], usually require an agile and flexible production line (with a strong emphasis on innovation), to remain relevant and profitable in the market [12]. Automated operations require lesser number of human workers in food processing lines, which also contributes to the reduction in contamination by transient food borne microbes and foreign matter of human origins. This increases the shelf-life of food and also mitigates the indiscriminate harm it could cause to the final consumers [13].

In addition to making the product more shelf stable, food processing increases the usefulness and palatability of the food. Common industrial processes employed to enhance the quality of raw food products include milling, cooling, heating, smoking, fermentation, canning, and extrusion cooking. Additionally, preservation methods such as smoking, brining, pickling, and the use of chemical additives, antimicrobials, and antioxidants are widely utilized [14]. All the aforementioned steps vary depending on the particular product being processed, consumption requirements, and the desired end result required by the consumer. This diverse range of processing variations, make food production a multifaceted and dynamic field with extensive advances in research and technology. Therefore for the sake of brevity, we are limiting the scope of this paper to cover the technological advances in the primary processing of food. Primary food processing involves the initial handling and treatment of food after harvesting. This includes activities such as cleaning, sorting, initial packaging, and other essential tasks to prepare the food for storage or transportation [15].

The equipment for automating primary processing of food typically entail sensing systems, actuation systems, data processing and storage systems, communication systems and user interfaces [16]. The sensing systems detect the presence or absence of certain specific physical or chemical properties, along with the product's position and physical state. Some of the sensory systems utilized in food processing are temperature indicators, humidity sensors, pH indicators, gas sensors, pesticide detectors, pathogen detectors, and (most predominantly) imaging sensors [17]. The actuation system comprises the elements which bring about physical changes (either in the form of value addition or material handling) in state of the product being processed. They broadly consist of SPMs, robot actuators, conveyor systems and transportation equipment.

Primary handling in the food sector has enormous potential for robotic automation, but it needs specifically developed solutions [18]. Primary food handling with robots presents difficulties due to the characteristics of the food. Foods have variability in shape, structural integrity, and size (as represented in Fig. 1), requiring end-effectors that can tolerate these variations. Additionally, products can be susceptible to damage or may be fragile, limiting the applicable working pressure of end-effectors. The lack of knowledge about potential robot applications, the limited functionality, the lack of grippers, and their cost impede the use of robotics in this sector. Within the food and beverage sector, certain sub-sectors such as fruit and vegetable processing have a lower degree of automation despite their economic importance [19]. These sub-sectors have a more significant opportunity to automate their production processes with robots.

In food processing, robots boost productivity by cutting costs, reducing waste, and saving time and space. They also improve product quality by providing accurate assessments and eliminating errors. Additionally, they create a better work environment by allowing employees to focus on skilled tasks and avoid dangerous or repetitive work. Robots increase production flexibility, respond quickly to market demand, and ensure food safety and hygiene standards are met [20]. Yet no universal robot end-effectors are available, and an optimal end-effector should be designed for every product and application process. An adequate end-effector for food in the industry is challenging using a standard end-effector because food can be soft, fragile, sensitive to damage, has wide tolerances, and has complex shapes and sizes.

Alongside robots, another emerging technology for fresh food processing is machine vision. It essentially incorporates hardware and software components that harmonize together to acquire, perceive, and interpret visual information. Its importance for fresh food processing stems from several advantages such as (i) food safety, owing to its non-invasive nature as it processes only visual information, (ii) high inspection speed, leading to higher throughput and reduced production costs, (iii) better waste management, by increasing the accuracy of identifying the healthy produce, (iv) economically affordable, especially in the long-term, as compared to a human operator, and (vi) product traceability by identifying and tracking food items as they move through complex production and supply chains.

While automated manipulation of food products in primary processing is undeniably useful and essential, it presents numerous challenges primarily due to the bio-physical and

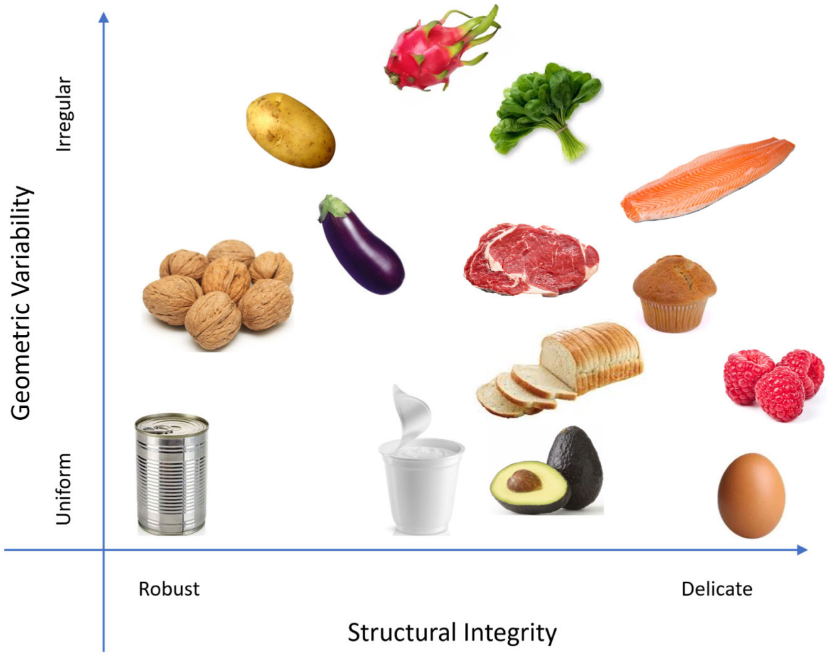

FIGURE 1. Graphical representation of the variability in geometry and structural integrity for diverse representative food items. Typically, the more irregular and/or delicate the food item is, the more challenging it is to manipulate it with robotic systems.

bio-chemical properties of the food products. Furthermore, establishing a well integrated sensing and actuator system, capable of performing real-time computational estimates and motion planning, requires high amounts of expertise, time and capital. Another factor which impedes the implementation of automated solutions is the range of diversity in the characteristics between seemingly similar food types, warranting nuanced solutions for individual scenarios, depending on the product and the processes to be performed on it.

So far, the literature pertinent to food processing has accumulated an interesting amount of research, which has been documented in several surveys. However, these are either reviews of existing technologies for a particular type of food such as meat [21], poultry [22], fish [23], fruits and vegetables [24], or survey a specific technological solution as applied to general food processing [25].

To the best of our knowledge, up until the date of publishing this manuscript, there is no research that surveys existing machine vision and robotic solutions for primary food handling and packaging. We were able to ascertain this by performing specific keyword searches, as specified in Table 1 on the Scopus database [26], comparing the Abstract, Author keywords, and Indexed keywords of all the articles in the database. The frequency of the keyword appearance and their co-occurence networks were visualized in Fig. 2 and Fig. 3 using a software tool - VOSviewer [27]. The VOSviewer visualizations depict the 'Network Visualization Comparison', and the 'Density Visualization Comparison'. The Network Visualization Comparison refers to the analysis of the structure and connections between items in a map, highlighting the number of nodes, the strength of links, and the overall network density to understand the extent and cohesion of research in a given area. The Density Visualization Comparison focuses on evaluating the concentration of research activity by identifying hotspots in the map, where higher densities indicate more frequently occurring terms or topics, and lower densities reveal underexplored areas. Clustering in network visualization helps identify groups of closely related items, highlighting the main topics or themes within the research area (using color coded grouping). Whereas in density visualization, clustering reveals areas of high research concentration, indicating well-explored topics and helping to pinpoint gaps in the literature.

The comparison of VOSviewer visualizations between the two conditions clearly highlights the disparity in research focus. Fig. 2, which examines robotics, machine vision, and their application in the food industry, shows a sparse and less connected network (left), indicating a limited number of review articles and fragmented research in this niche area. The lower density of terms and fewer clusters further reinforce the idea that this specific intersection has been explored very minimally (right), with only 24 documents identified in the search. In contrast, Fig. 3, focuses on robotics and machine vision without the food industry context, presents a much denser and highly connected network, with 358 documents identified. The presence of numerous strong clusters and hotspots indicates a well-established and widely researched field. The lack of significant overlap with food-related terms in this broader research stresses the conclusion - that while robotics and machine vision are

TABLE 1. Keyword comparison on Scopus database.

Keywords for article type	Keywords for robotics	Keywords for gripper	Keywords for vision	Keywords for food	Number of articles retrieved
review OR (literature AND review) OR survey	robot OR robotics	gripper OR (end AND effector) OR tool	vision OR (machine AND vision) OR (computer AND vision)	food OR (primary AND processing)	24
review OR (literature AND review) OR survey	robot OR robotics	gripper OR (end AND effector) OR tool	vision OR (machine AND vision) OR (computer AND vision)	-	358

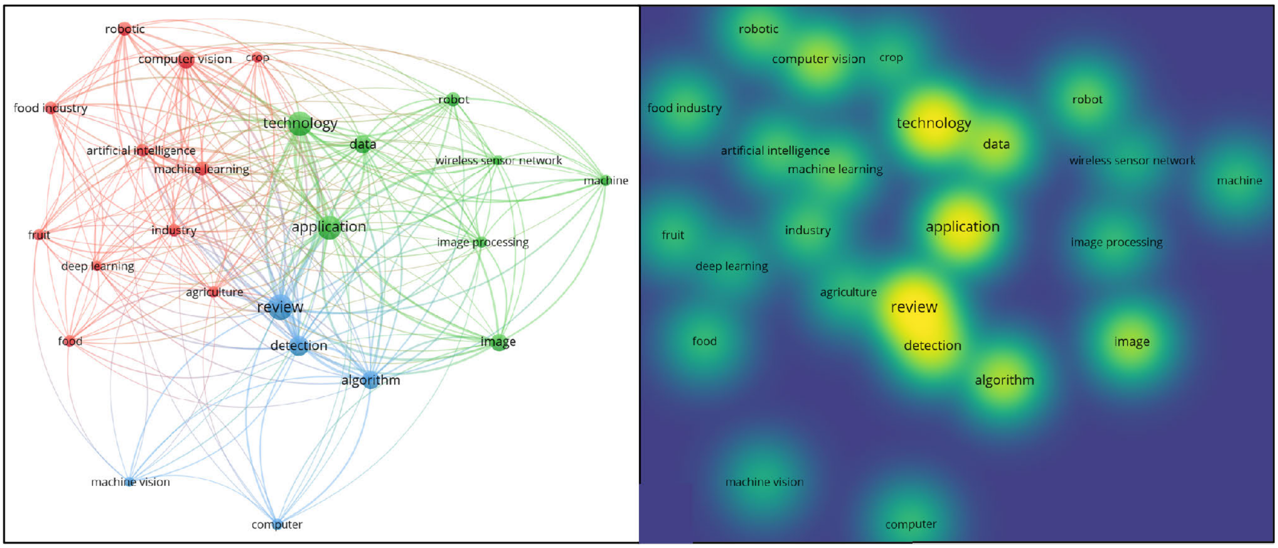

FIGURE 2. VOSviewer visualizations of the network visualization comparison (left) and the density visualization comparison (right) for reviews including the keywords for robotics, vision and food.

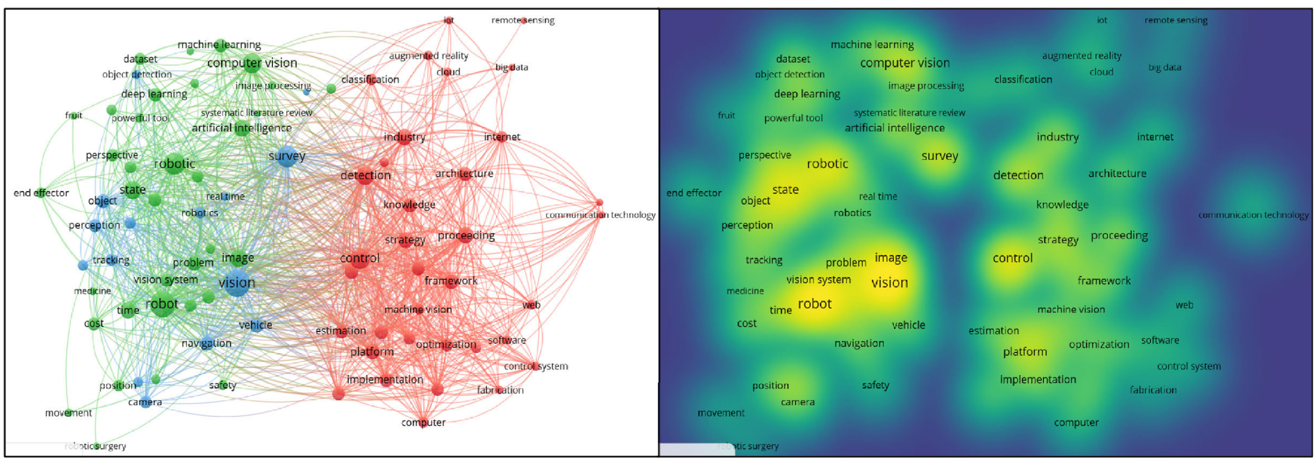

FIGURE 3. VOSviewer visualizations of the network visualization comparison (left) and the density visualization comparison (right) for reviews including only the keywords robotics and vision. Without including food.

extensively studied, their specific application in the food industry remains underrepresented in the literature.

This work aims to bridge this gap. We showcase a landscape of existing vision and robotic systems currently used in primary food processing and their challenges in the form of a technical review. In fact, different issues must be considered: primary food is prone to deformation and bruising, and typically exhibits a shorter shelf-life (e.g., fresh versus dried fruit), which suggests that their handling must be timely, accurate and non-destructive.

The remaining sections of the paper are structured as follows. Section II deals with the smart sensing element of the food process automation system- with an emphasis on machine vision systems. This section further touches on the various challenges impeding installation and operation of vision systems; briefly introduces Artificial Intelligence (AI) and it's impact on the system; and it also outlines existing contemporary research in machine vision systems to sense fresh produce and animal products. Section III discusses the hardware aspects utilized in food processing system which primarily comprises robotic systems, end-effectors and material handling (transportation) systems. Section V highlights some insights regarding the existing literature and source materials, and provides a summary of the manuscript along with our concluding remarks on the current state of the industry and its future potential.

II. VISION SYSTEMS

A. MACHINE VISION: A BACKGROUND

Machine vision (MV) is an advantageous tool that can be harnessed to automate the inspection of food and agricultural products. It provides an automated, non-destructive, and cost-effective technique to accomplish quality inspection, which has found a variety of different applications in the food industry. The inspection approaches are normally based on image acquisition, analysis, and processing. A typical MV system incorporates four interdependent components:

1) LIGHT SOURCE

Light is a fundamental component in many vision systems in order to ensure that the objects/scene under exposure are clearly visible and enable an accurate image analysis. In this respect, important features to consider in lighting source are the light intensity and the light uniformity across the scene. Light intensity should not be too low or too high to prevent dark images as well as undesired saturation effects. Light uniformity helps to surpass glare and shadow effects.

Another important parameter to take into account is the energy consumption especially in large-scale application. However, the parameters of the lighting source depend tightly on the requirements of the application in hand. The commonly used lighting sources are (i) Fluorescent, which provide consistent and even illumination, (ii) Quartz Halogen, which are noted for color temperature stability, (iii) LED (Light Emitting Diode), which are widely used due to their energy efficiency and versatility, (iv) Metal Halide (Mercury), which are used for high-intensity applications, and (v) Xenon, which are suitable for short-duration and high-intensity bursts. Fluorescent, quartz halogen, and LED lighting sources are the most widely adopted in MV applications. For more in-depth analysis, we refer the reader to [28], [29], [30], [31], [32], and [33]. A comparative graph among lighting sources is given in Fig. 4.

2) ACQUISITION SENSOR

Cameras are the eye of any MV system since they provide the visual input that can be processed and analyzed by the vision software to further extract and analyse the required

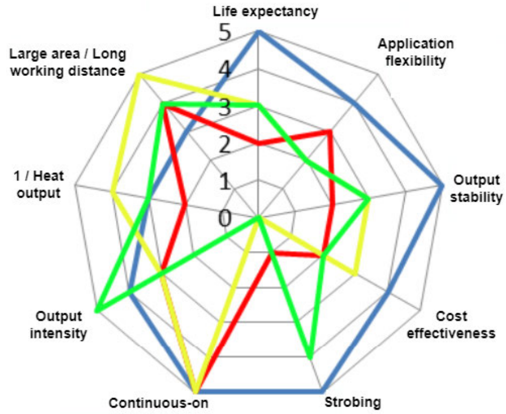

FIGURE 4. Comparison of common MV lighting sources on a scale of 5. Figure data sourced from [34].

output (e.g., quality control, inspection, measurement, identification). In particular, they can see object details that are too small or too fast to be captured by the human eye, often with accuracy and efficiency. Standard cameras acquire RGB images through three wideband filters capturing the short, medium and long wavelength of the light and encoding the responses in the RGB color space. RGB images are used in many color-based applications, such as fruit detection [35], [36]. Multispectral cameras capture information that is not visible to a typical RGB camera. They incorporate narrowband filters to divide the light into more than three channels, such as near-infrared (NIR), or thermal. Multispectral sensors can be tailored to applications such as identifying fresh food diseases, maturity, and mapping [37], [38]. Fig. 5 shows some examples of sensing solutions.

3) PROCESSING UNIT

The processing unit reads, analyzes and makes appropriate decision pertaining to the task of interest based on the images acquired by the camera sensor(s). On the other hand, software programs are normally ad-hoc to the addressed problem and can be broadly split into two lines, namely (i) traditional vision algorithms that deal with object edges, texture, pixel intensity and handcrafted features [47], and (ii) recent data-driven methodologies that learn from data in order to approach the problem at hand [48], [49]. These latter have demonstrated cutting-edge accuracy across various applications. Therefore, the processing unit typically comprises hardware devices and software that run on them. The hardware components may involve central processor (CPU) that can process data as in [50]. CPUs are normally adopted in vision tasks that implement traditional non-demanding methodologies. However, recent deep learning methodologies normally require specialized graphical processing units for a real time performance as in [51] and [52]. Yet, the choice of the processing unit depends on the complexity and requirements of the application and can affect the speed, accuracy, power consumption, and cost. In order to clarify this, in Table 2 we provide a landscape of

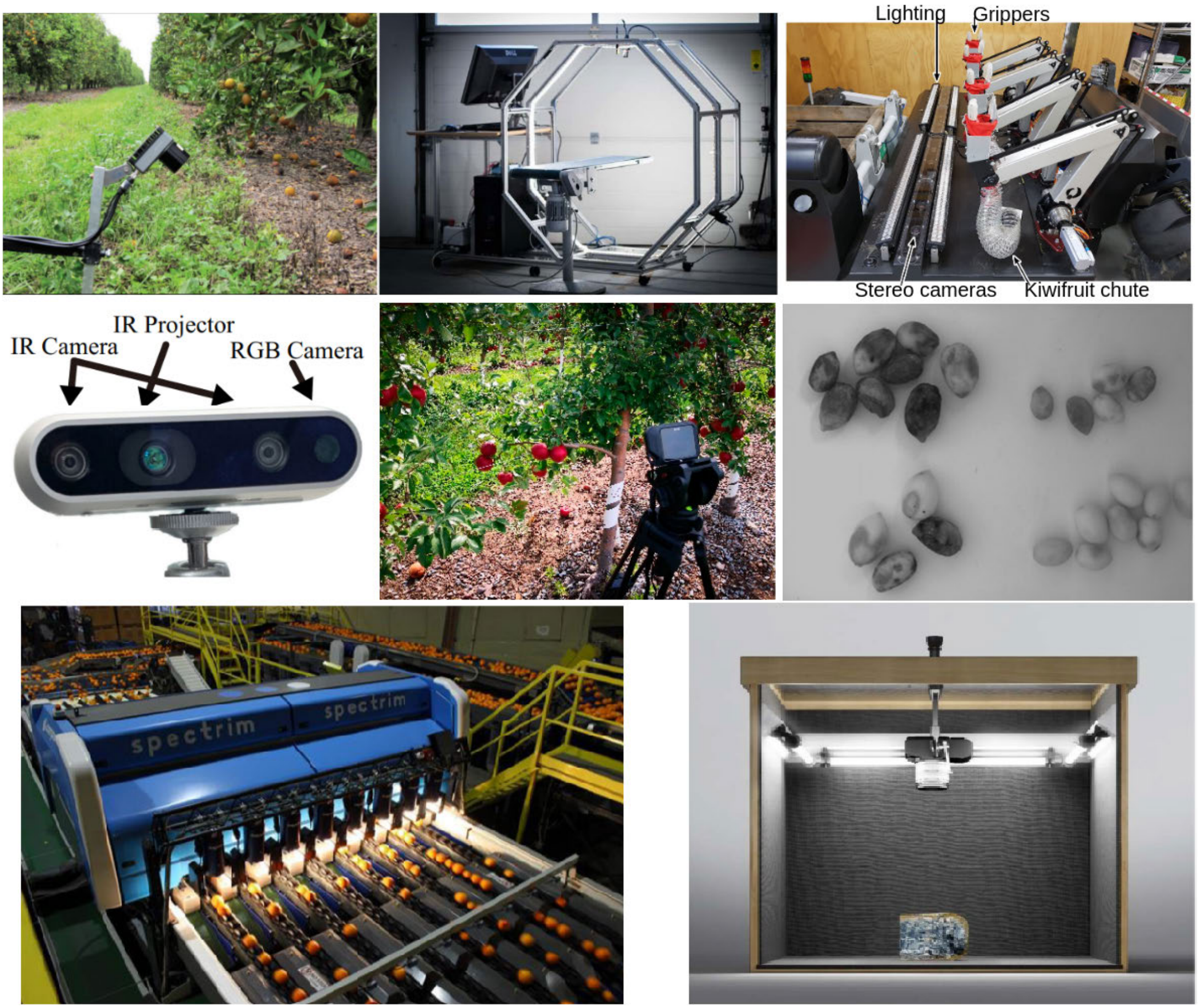

FIGURE 5. Examples of common sensing solutions in a MV system (first two rows) and enclosure-based vision systems (last row) where cameras and light sources are normally mounted inside an enclosure through which passes the product under inspection [39], [40]. Row 1 (left to right): RGB [41], multi-RGB [42] and stereo vision [43]. Row 2 (left to right): Depth camera [44], multispectral sensor [45] and Infrared [46].

machine vision-based analysis systems that involve different processing units for various types of food such as poultry, beef, fruits, and fish.

4) COMMUNICATION MODULE

Communication module is an essential instrument as it enables a seamless flow of data between the various parts of a MV system. It also controls how input and output information is synchronized in coordination with external collaboration devices (e.g., a robotic arm that operates and executes item handling commands and instructions that are output by vision system). The communication module may adopt various protocols which have evolved over time to meet the growing demands of higher resolution, faster frame rates, and increased data transfer speeds. Thus, wired and wireless communication standards are envisioned.

B. CHALLENGES OF MV SYSTEMS

Apart from the initial cost which can be compensated with the long-term benefits of a MV system, there are several bottlenecks that may eventually rise during and after the installation of a MV solution. For instance:

1) CONFIGURATION COMPLEXITY

Traditional computer vision software rely on handcrafted parameters (e.g., pixel segmentation thresholds) that are normally determined offline based either on (i) a limited number of data (e.g., images) or (ii) a large number of data that is repetitive (i.e., statistically highly consistent) and does not necessarily mimic the real-time scenario of the application. In both cases, when challenging and unseen examples (outliers) are presented to the system, it fails to perform efficiently. This problem is less prevalent

TABLE 2. Summary of processing units adopted in various use-cases.

Product	Task	Processing unit	Reference
Pears, apples	Ripeness determination, harvesting	NVIDIA Jetson AGX Xavier	[44]
Red and green tomatoes, grapes	Sorting	Raspberry Pi	[53]
Date fruit	Grading, harvesting	Intel Xeon E5-2600 CPU (28GB RAM), Nvidia GeForce GTX 1060 (6GB)	[51]
Mutton	Authenticity assessment	2.60GHz CPU (3.2GB RAM), Nvidia GeForce RTX 3060 (12GB)	[54]
Grapes	Yield estimation	Raspberry Pi	[55]
Tomatoes	Sorting	i5-5200U 2.20GHz CPU (4.0GB RAM), NVIDIA GeForce 930M GPU	[56]
Trout Fish	Processing (belly cutting, beheading, gutting, and cleaning)	Programmable logic controller	[57]
Eggs	Grading	Raspberry Pi	[58]
Tomatoes	Sorting	Raspberry Pi	[59]
Coffee	Grading (roast quality)	NVIDIA Jetson Nano (4GBRAM)	[60]
Fish	Grading	Desktop PC with Intel® 1151 CoreTM i7-9700 3.0GHz CPU, NVIDIA GeForce RTX 3070 8GB GDDR6 GPU	[61]
Tomatoes	Grading	Intel Core i5-3317U	[50]
Atlantic salmon	Cleaning, grading	Intel i5-6300 CPU	[62]
Chicken breast	Quality assessment	Intel (R) i7-10700 2.90GHz CPU, NVIDIA Quadro P620 GPU (8GB)	[63]
Hanwoo beef	Grading	Intel 2.6GHz CPU (8 cores, 16GB RAM)	[64]
Chicken breast	Freshness assessment	Intel Core i5-9300H 2.40GHz CPU (8GB RAM), NVIDIA GeForce GTX 1650	[52]

in learning-based methodologies that are trained on large volumes of data, where the parameters are learning in an automatic fashion.

2) SCALABILITY

This may occur when a MV solution is setup at a production line without prior long-term planning to scale it up across the production facility. This, in turn, poses space and cost management difficulties.

3) MAINTENANCE

Like any other system, MV systems require monitoring to ensure that the whole pipeline manifests no anomalies. For instance, this may entail the implementation of image quality assessment mechanisms, which help evaluating how well the acquisition sensor and the lighting sources are functioning.

4) SOFTWARE UPDATE

Data-driven computer vision techniques that require training may require fine-tuning with new data to improve their performance. Furthermore, they need to be retrained on newly introduced item categories (e.g., a system that was trained to detect red apples can be fine-tuned to accommodate green apples too).

5) ROBUSTNESS TO REFLECTIVE OBJECTS

This poses a major challenge as shiny items may be handled less accurately leading to error. This problems even magnifies in fast production lines.

6) HANDLING LIGHT CONDITIONS

In view of the illumination component, it is noteworthy that in some applications, even if the item of interest is exposed to artificial illumination, the output image may still require further postprocessing. In particular, the uncontrollability of the natural light in outdoor environments (e.g., acquisition of images of fruits in the field) represents a challenging issue in MV, since image quality strongly depends on the illumination, backlight, shadows, reflections, as well as smooth or abrupt variations of light intensity and chromaticity caused for instance by time and weather changes. These often occur in natural scenes and determine undesired artifacts that hinder both human and machine image understanding [65]. To this end, enhancement algorithms are necessary to increase the image quality and thus consolidate further decision-making (i.e., quality grading). These algorithms basically process the image channels or brightness and increase the brightness of dark areas while preserving that of bright regions, magnify the image edges and colorfulness, while decrease possible chromatic noise. Some examples of image enhancers are histogram-based equalization techniques, e.g., [66], [67], Retinex and Retinex-inspired approaches performed at single or multiple scales and implemented with traditional or deep learning based models, e.g., [68], [69], [70], [71], [72], [73], [74], [75], [76], multi-level enhancement algorithms [77], [78], [79], other deep learning techniques, as in [80], [81], and [82]. The choice of a specific enhancer is generally driven by the image and application at hand. To this purpose, it is important to take into account possible a-priori information regarding the illumination source and the materials composing the scene, verifying the hypotheses under which the enhancer works and - in case of applications with time constraints - the algorithm complexity and execution speed. In indoor scenarios, light must be bright enough to allow visibility and detection of object details, and at the same time, it must minimize reflections as well as saturation. Since colors strongly depend on the light and on the camera's physical features and setting, images of the same object acquired under different lights and/or by different cameras may manifest differ colors. In this case, color transformation and gamut mapping are necessary to process colors effectively against light and camera changes [83], [84], [85], [86].

C. ARTIFICIAL INTELLIGENCE

Before we delve into existing software methodologies for primary food processing, we deem it necessary to explain briefly three common techniques, namely artificial intelligence, machine learning, and deep learning. Artificial intelligence (AI) belongs to the processing part of a MV system. It has become ubiquitous in many industrial applications [87]. AI attempts to carry out tasks, solve problems and make decisions that often require human-like reasoning and intelligence such are visual and audible perception [88], [89], [90]. AI is an overarching term that encompasses other sub-fields. Two of the most applicable sub-fields in recent days are machine learning and deep learning:

1) MACHINE LEARNING

A major subset of AI that enables machines (e.g., computers) to learn from data, draw patterns, and make decisions with limited or no human interference. In other words, machine learning gives machines the potential to decipher, estimate and interpret from data on their own without being explicitly programmed. Depending on the nature and complexity of the problem, as well as the quantity and quality of data, three main learning algorithms can be employed, namely (i) supervised learning, where both input data and its labelled output are required, (ii) unsupervised learning, in which only input data are envisioned and typically explored via clustering techniques to discern correlation patterns, and (iii) reinforcement learning, where data and abstract labels (e.g., yes, no) are provided to the algorithm to learn potential actions and decisions to take. In this context, machine learning has found its way to many application domains such as finance [91], healthcare [92], manufacturing [93], logistics [94], industry 4.0 [95], and climate science [96].

2) DEEP LEARNING

A subset of machine learning that consists in training a deep Neural Network by leveraging plenty of data records. Deep networks consist of interconnected nodes that are distributed according to three types of layers, namely (i) an input layer that receives the input (e.g., image, text, voice), (ii) intermediate hidden layers that extract and process features of the input and pass them forward to an (iii) output layer that maps these latter to a desired output according to the problem being tackled (e.g., locations and classes of objects in an image, prediction of a future state). This type of network is termed 'deep' as they involve abundant hidden layers that enable the interpretation of complex cues in the input data. Therefore, such networks are trained with large amounts of data, which renders them suitable to downstream tasks via transfer learning where a specific model [97], [98], [99] that was trained on a particular task (e.g., image recognition) is fine-tuned to fit another task (e.g., object detection) [100]. This underlines why deep learning has become a cutting-edge technology in many vision tasks [101].

In particular, one important task that relates to machine vision for product inspection and quality control is object detection, which entails the determination of the location and often the class label of a certain object of interest in the scene. Object detection has been gaining increasing attention over the last two decades. To highlight this, we depict in Fig. 6. Further, in Table 3 we highlight the key-differences between deep learning and traditional handcrafted feature analysis. We also illustrate the timeline development of object detection using traditional schemes versus deep learning in Fig. 7.

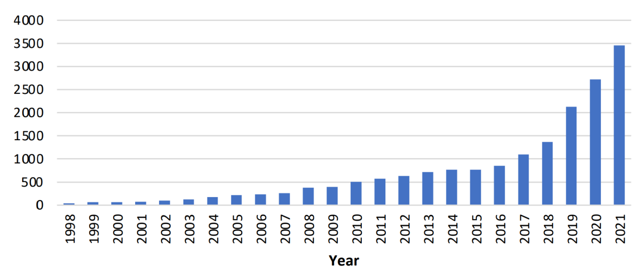

FIGURE 6. Publication trend on the task of object detection over the last two decades. Figure data sourced from [102].

D. MV FOR PRIMARY FOOD PROCESSING

Considerable research has been developed in the relevant literature so far regarding the primary food processing. It is to note, however, that MV solutions depend on the

TABLE 3. Key-differences between traditional engineered features and deep learning.

Attribute	Handcrafted	Deep learning
Data requirement	Suitable for tasks with limited data	Suitable for tasks with abundant data
Computational efficiency	Less demanding	Depends on the used hardware
Computational resources	Less demanding	Specialized processors (e.g., graphics processing units) often required for optimal performance
Task representation	Limited capability to capture complex cues in the data	Far better in pinpointing complex data patterns
Design	Require domain expertise and trial and error procedures	Automatic end-to-end learning without manual engineering
Versatility	Typically not, as they are task-specific	Adaptable to a wide range of tasks, enabling knowledge transfer and distillation

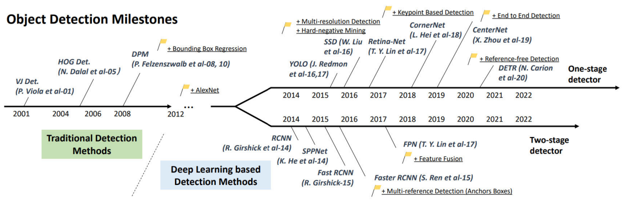

FIGURE 7. A timeline progress of object detection, traditional methodologies vs deep learning. Figure data sourced from [102].

nature of food product. For example, the components of a vision system to grade fruits on-tree are different than those envisioned to do the grading indoors in a production chain (i.e., due to differences lighting and available space for instance). Moreover, the analysis of fruits and vegetables versus meat, poultry and fish is subject to several key differences, examples include:

- Viewpoint: fruits like oranges and apples and vegetables such as tomatoes exhibit a spherical shape which calls for multi-view analysis in order to cover the whole skin. On the other hand, steaks and cuts of meat, chicken or fish require the analysis of one or two sides only. This implicates different image acquisition strategies.
- Texture: grading fruits is normally relevant to color, size, and shape, bruises/blemishes, while grading meat, poultry or fish may involve thickness and fat content within the tissue. This entails different grading algorithms.
- Internal quality: internal quality of fruits and vegetables considers factors like ripeness, and sweetness. For meat, poultry and fish, tenderness and juiciness are common properties. This involves different sensing solutions (e.g., regular RGB versus Multispectral sensors).

In the next sections, we survey existing MV approaches for fresh produce (e.g., fruits and vegetables) as well as meat/poultry/fish, respectively.

1) MV FOR FRESH PRODUCE

MV can boost the precision and speed of fruit and vegetable inspection, yet increasing throughput. Common tasks include counting and yield estimation, defect and disease detection, grading, packaging inspection. Some of these tasks may be performed in outdoor environments, while others may be carried out in indoor facilities, depending on the application. For instance, on-tree plum fruit detection was addressed in [103]. In particular, an altered version of a sate-of-the-art deep model, namely YOLOv7, was applied on high-resolution images of plum fruit and scored plausible results. Postharvest storage is a sensitive step in the fruit supply chain due to a number of factors such as humidity, temperature and ventilation. Adequate storage conditions mitigates losses and ensures uninterrupted supply. Pre-storage fruit analysis can help identifying premature diseases. Computer vision was explored in [104] for blueberry disease classification. After image acquisition, single blueberries are segmented, followed by traditional texture, intensity and geometrical feature extraction. Next, several classification techniques were assessed for the classification task, including Support Vector Machines and Linear Discriminant Analysis which performed the best. Powdery Mildew disease detection in strawberries was considered in [105], where a mobile mini vehicle that incorporates mainly two optical sensors to increase the field of view for image acquisition, a GPS module for mission planning, a laptop for data processing, and an artificial cloud lighting made of black cloth to prevent direct sunshine. Communication between the GPS system and the laptop computer was established via a serial link setting. Color co-occurrence matrix was explored for feature extraction, and the features are learned by means of an artificial neural network. Tomato maturity (Roma and Pear varieties) was assessed in [106] by exploring color features.

Regular visible light sensors have been used in many MV systems to inspect visible produce conditions (i.e., size, counting, blemishes). However, there are numerous plant diseases that cannot be captured by the visible spectrum and require in-depth imaging. For example, multispectral imaging was applied in [107] for plant disease detection in tomato, potato and papaya leaves, where convolutional neural networks and vision transformers were exploited for the detection task. In [108], a solution that involves multispectral imaging (covering 25 wavebands) and deep learning was adopted for defect detection in potatoes (including five types of defects, i.e. germination, common scab, bug-eye, dry-rot, and bruise) and yielded a mean average precision of 90.26%. Quality grading of apples was considered in [109] by means of multispectral imaging and deep learning. In this regards, while opting for only one modality (i.e., RGB or multispectral) seems to satisfy the requirements of many MV tasks for fresh produce processing, a multimodal approach can benefit many other use-cases. For instance, hyperspectral, 3D, and X-ray imaging were combined in [110] for quality inspection of onions, and yielded a classification score of 88.9% when classifying healthy and defective onions. Although the proposed classification system achieves plausible results, it is to note that recent deep learning techniques are prone to introduce a significant improvement. For examples, RGB and Hyperspectral imaging were leveraged for banana grading into 3 classes in [111], and a deep learning model fed with this bi-modal data was able to reach and overall accuracy of 98.45%.

Produce yield estimation is pivotal for logistic planning. For instance, storage space, and transportation means depend depend on the quantified yield (i.e., over-estimated yield leads to unnecessary extra spending, while under-estimating the yield causes space and transportation shortages at later stages). For instance, kiwi fruit detection and counting for yield estimation was addressed in [112]. It involves an optical sensor mounted on a tractor that surveys the area of interest at low speed. Afterwards, the acquired images are fed to a software that implements image pre-processing, stitching, and fruit counting algorithms and outputs an estimated yield. Since kiwi trees develop a foliage canopy that blocks sunlight, the fruits were exposed to a LED source mounted upside down next to an optical camera to enable fruit detection. An over-the-row MV system was developed in [113] for apple fruit counting and yield estimation. It comprises a tunnel-like housing, RGB 3D sensors, a LED lighting. Interestingly, dual imaging to capture opposite sides of the apple trees was compared to regular single side imaging, and they score 82% and 58% crop estimation accuracies, respectively. The advantage of combining housing structures and uniform LED lighting stems from their independence from natural lighting conditions as they can be used during daytime and nighttime.

Yet, it is worth-noting that, depending on the specifics of the application, visual inspection of produce can be carried out either in the field or in the production facility. This implies different sensor configuration and placements as well. For instance, in-lab MV systems normally rely on artificial lighting which does not impose constraint on the usage time. On the other hand, some on-tree inspection systems can perform only during daytime, while other systems can work during daytime and nighttime (e.g., Fig. 8). Furthermore, indoor MV systems are normally deployed with an enclosure/housing that accommodates the vision sensor and the lighting source in order to enable uniform lighting conditions (e.g., Fig. 5 bottom row). Another feature that distinguishes indoor MV systems from outdoor systems that the camera and lighting pose. In particular, most indoor systems mount cameras and lighting sources in a top-down position as the products under inspection typically roll on a production platform (e.g., conveyor belt), whilst in-field MV solutions are deployed various setups depending on the subject canopy. For example, kiwi vine canopies require a bottom-up sensor and lighting implementation, while mango or apple trees may require a side-mounted camera (e.g., Fig. 8).

2) MV FOR FISH, POULTRY, AND MEAT

It is evident that fish, meat and poultry are far more sensible than fresh produce as they have shorter shelf life and are more subject to contamination. Moreover, they differ from fresh produce in the sense that fresh fruits and vegetables are typically harvested and subsequently processed. By contrast, processing fish for instance, may involve extra pre-processing steps such as removing the head and tail parts, trimming the fins and gutting.

In this context, the work in [115] develops a MV system to determine the orientation and cutting points in trout fish. It comprises a housing with a RGB sensor and LED lights both mounted on the ceiling of the case in top-down position, a computer that incorporates the imaging modules, and a power supply. In order to acquire the images, the trout subject is laid down at the base of the stainless steel case, while the LED lights and the camera are turned on, once the images are acquired they are communicated to the computer. This latter consists in traditional thresholding techniques for trout segmentation from the background. Once segmented, the centroid and orientation of the fish are determined. In [116] MV was applied to estimate the total length of fusi form fish by means of regional convolutional neural networks based on optical sensors, where the fish size was converted from pixels to real world via ArUco markers. 3D imaging was explored in [42] for quality grading of Atlantic salmon. Flatfish grading with MV was addressed in [117]. It consists mainly of three components, namely a low-cost camera, LED lights and a dark room to prevent shadows from compromising image quality. The vision software implements traditional thresholding and morphological filtering steps. Near infra-red was employed in [118] for herring fraction grading into three classes (milt, roe and waste) based on a multi-class support vector machine fed with a features like width and height. The developed system was able to classify roe class from the other two, while it suffers to separate milt from waste samples. This might be mainly due to the extracted features that are not representative enough of the three classes. A vision pipeline was devised for fish grading according to pesticide exposure in [119]. In particular, the eye tissue of the fish was determined as a region of interest as fish eyes manifest changes when exposed to pesticide. Next, statistical

FIGURE 8. On-tree produce assessment instances [112], [114]. The camera and light source position depends on the growth side of the produce. Some systems perform independently of sunlight, while others work better during daytime.

features are extracted from this region and fed to different machine learning classifiers for further classification, where random forest turned out to be the best classifier. Fish eye region was also tailored in [120] for freshness estimation. Gaping blemishes detection in salmon was explored in [121], where traditional histograms of oriented gradients features were compared against convolutional neural network features and these latter demonstrated superior performance. Hyperspectral imaging was studied for differentiation of organic and conventional farm-raised salmon fillets in fresh and chill-stored conditions in [122], based on three machine learning classifiers and highlighted the potential of hyperspectral imaging of these two fish varieties. Freezer burn is a leathery condition that occurs when air reaches and dries the surface of food, causing color changes. It was studied in [123] by comparing hyperspectral to RGB imaging of frozen salmon, and hyperspectral imaging performed far better.

In this regard, processing chicken samples from a MV standpoint differs from processing fish in several aspects. For example, color is a key-factor when adopting visible RGB imaging. Shape is another feature to consider when processing chicken parts. In particular, chicken portion sorting (i.e., breast, leg, fillet, wing, and drumstick) was addressed in [124] via MV with an optical sensor. Handcrafted features based on geometrical aspects, colour, and texture are extracted from the images and fed to different classifiers for the sorting task. An overall accuracy of 93% was achieved with a conveyor belt of 0.2 m/s. Although the performance of the developed system is reasonable, it was not validated for higher conveyor speeds that are normally adopted in industrial settings. Wooden breast muscle condition detection was conducted in [125] by means of global shutter RGB imaging from a side view of chicken fillets passing along a conveyor belt. Fillet segmentation consisted of simple global thresholding, combined with hole filling and median filtering. Fillet curvature was determined by applying second degree polynomial fitting. In [126], weight estimation of broiler carcass was studied with 3D imaging. In particular, the carcass is segmented into 4 parts, namely drumsticks, breasts, wings, and head/neck. Afterwards, 2D image geometric features are drawn and fed to different regression models for weight estimation. Hyperspectral imaging was employed in [127] for the assessment of egg quality (i.e., freshness and defection) by means of deep learning. Egg quality indicators such as geometric dimensions, shape index and the mottling grade were explored for grading the exterior quality of eggs in [128].

With respect to fish and chicken, beef offers a different color and texture profile, which may imply the implementation of different techniques. In [129], beef meat freshness was classified according to two classes- fresh and spoiled. The developed MV system consists of an enclosure, at the top of which a camera and fluorescent lights were mounted in top-down position and 45 degree incidence angle, respectively, a digital signal processor and a computer. To tackle the classification task, color and texture features are extracted from the images and fed to probabilistic neural network and linear discriminant analysis for decision making. It was found that using both color and texture features outperforms the scenario where each of them is used individually. Nevertheless, the study remains inconclusive as the number of beef samples used in the experimental analysis is somewhat limited. Further, as aforementioned, MV solutions that draw only handcrafted features from the subject images often encounter generalization bottlenecks when deployed in different setups with domain shifts (e.g., different lighting, different sensor). Beef cut classification was addressed in [130] by means of multispectral imaging and machine learning. Precisely, beef cuts were exposed to a lighting source, and a top-down multispectral sensor (500-800 nm) was used to capture six-band images. Several feature types were extracted from the acquired images and fed to various classifiers including linear discriminant analysis. support vector machine, and random forest (RF). A combination of multiple features outperformed each feature when used individually. In Table 4, we report several MV works and their components for different food item analysis.

It is worth-noting that, apart from the choice and quality of imaging sensors, the quality and uniformity of lighting devices, the processing algorithms play a pivotal role in the precision of the decision-making process. In particular, manually engineered feature extraction techniques differ drastically from state-of-the-art deep learning methodologies in many aspects. In this context, the choice among these two options depends on many criteria such as speed, cost, data availability, among others.

In this context, depending on the use-case requirements (e.g., product grading only versus grading and packaging), a MV system can be standlone, or execute tasks in coordination with another system. For instance, many industrial setups involve a vision system that discerns visual properties (grade, size, color, among others) of a certain item of interest, as well as a robotic system in order to handle the products according to the visual attributes inferred by the vision system (e.g., place the high-grade items into a package and discard the low-grade ones). We provide in Fig. 9 an abstract depiction of a MV system in collaboration with a robotic handling solution.

III. ACTUATION SYSTEMS

This section deals with the elements of the food processing system, which physically manipulate or bring about a change in state to the food product. To align with the scope of the paper we will only emphasize on robotic systems here, and they typically include robot manipulators, end-effectors and material handling (transportation) sub-systems. Food grade material complying with the European Food Safety Authority (EFSA) should be the only material considered for constructing the surfaces of the physical actuators, which come in contact with the food [135]. The material property would vary depending on the application, compatibility with the food product and sanitary design features, and any other material which is unapproved must be strictly avoided [136].

A. ROBOT MANIPULATOR

Utilization of robot manipulators has been steadily increasing over the last decade [19]. Especially when considering the demographic and economic situation of the European food industry, as outlined in Section I, which includes lower median wages and a prevalence of low-skilled labor coupled with labor shortages, the need for integrating robotic manipulators in food production is highly warranted. The introduction of robots in the production line improves the repeatability of the process and ensures uniformity in the production standard. Another advantage of robots over other dedicated electro-mechanical machinery, is their capability to be reprogrammed to perform a wide range of tasks and varied operations, making it more attractive to medium scale producers with a wide variety of products/processes [137].

Robotic manipulators coupled with vision sensors or any relevant sensing element are prevalent in the food processing sector for a few commercial applications in the food industry. These include rapid pick and place of food products, palletising individual and bulk foods, and end of line packaging. The aforementioned operations require minimal product perception for real-time object manipulation, as the products typically handled have predictable physical properties and behaviors [137]. However, the robotic manipulation of food types which have unpredictable physical behavior, and fragile/delicate structural integrity is not as prevalent. These food types include soft fruits and vegetables, poultry products, fish and seafood and meat products. The technology for the complete butchering, portioning, packaging and material handling (primary processing) is still unattainable as a complete process. However, certain phases of the process are being automated and research is constantly evolving to utilize the advancements in sensor and end-effector hardware

TABLE 4. Summary of MV technologies.

Product	Task	Sensor	Illumination	Software	Reference
Apple	Detection	Thermal	Halogen lamp with filters to diffuse light	Texture features and Support vector machine	[45]
Onions	Estimate the weight, diameter and volume	Multimodal (color, hyperspectral, 3D, and X-ray)	Fluorescent lamps	Support vector machine with radial basis function	[110]
Citrus fruit	Counting	RGB	N/A	Retinex algorithm for image enhancement, Logistic and KNN and Bayesian classifiers (i.e., Citrus vs background) and Watershed algorithm for Citrus segmentation	[41]
Atlantic salmon	Grading based on wound and deformity	Three color CMOS cameras	LED strips containing multiple LED	Color and geometric features and Support vector machine with radial basis kernel	[42]
Olives	Detection based on the skin health condition	RGB and multi-Spectral	N/A	Edge detection and segmentation via connected components algorithm	[46]
Tuna and Salmon meat	Freshness classification	RGB	LED	Color historgrams and AutoML machine learning models	[131]
Salmon and rainbow trout	Slaughtering	Line-scan laser triangulation system	N/A	3D fish segmentation, median filtering for noise removal, geometric feature extraction for head/tail classification and Incision-point determination with linear discriminant analysis	[132]
Chicken pieces	Sorting	RGB	Linear LED tubes	Otsu method for segmentation, shape/colour/texture feture extraction, Chi-Square algorithm for dimensionality reduction, Partial least squares regression and Linear discriminant analysis and Artificial neural network models were used for classification	[124]
Eggs	Sorting	RGB	LED	Connected components for egg segmentation and geometric feature extraction for threshold-based sorting	[128]
Chicken meat	Springiness prediction	Hyperspectral	Halogen lamps	Partial least square regression and artificial neural networks for prediction	[133]
Beef and lamb	Grading	RGB	LED	Texture descriptors and Partial Least Squares	[134]

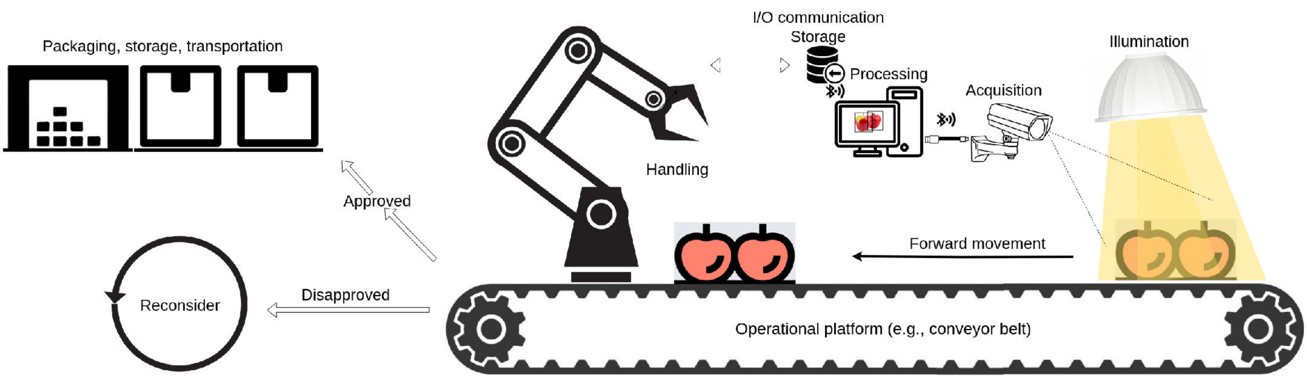

FIGURE 9. Components of a typical MV system in collaboration with a robotic system for fruit quality approval. The MV system is on the right hand side, and provides information to the robotic manipulator in order to pass the product under inspection on for logistic treatment in case of approval, and drop it off the processing line otherwise. The information might regard the grade of the product (i.e., according to criteria such as health status, size, ripeness) as well as location coordinates to enable its handling.

capabilities, along with evolving processing pipelines powered by AI. Advances are now being made in the processing of delicate fruits and vegetables [138], poultry processing [139], [140], and red meat processing [141], [142], [143], and recent research will yield viable solutions.

Robots come in various form factors and configurations, each tailored to specific tasks, with distinct advantages and limitations. Some types excel at particular tasks more effectively than others. There are four physical configurations or types of robots, which are prevalent in the food processing industry. These include:

1) SCARA ROBOT ARM

SCARA is an acronym for Selective Compliant Articulated Robot for Assembly. It has a work envelope which is similar to a lobed hollow cylinder [144], showcasing a large horizontal plane of operation with limited vertical movement. As the name suggests it is primarily used in assembly [145] and packaging applications [146]. SCARA manipulators are predominantly used in the electronics industry, with increasing utilization in the pharmaceutical and food production industries. Their kinematic structure makes them highly efficient for performing pick and place task, primarily owing to their dedicated prismatic joint, which provides the linear movement (whereas in robot configurations, this linear motion is achieved by the combination of multiple joints). Especially given the strides forward in their ease of cleanability and maintaining hygiene, SCARA robots are now finding applications in secondary food processing applications [147], [148].

2) ARTICULATED ROBOT ARM

Articulated robots or serial-link manipulators have a configuration, which is the most representative of an actual human arm in terms of capabilities, and thus are also referred to as anthropomorphic robots. Articulated robots typically have a spherical or hemi-spherical work envelope, and they have a larger work-envelope compared to other robot configurations, having similar physical dimensions [149]. This robot configuration is highly versatile, has a high degree of freedom (DOF) enabling it to perform complex operations, and is suitable for a wide range of applications including (but not restricted to) material handling, welding, painting, surgery, food industry, etc. [150]. Dual-arm articulated robots are emerging technologies capable of performing highly complex tasks akin to a human, and are used in specialized applications such as biomedical laboratories [151], cable manipulation [152] and cooking [153]. Articulated robots are used in primary food processing for performing tasks like cutting [154], sorting, packaging and food handling. The availability of hygienic robot manipulators which can be safely washed down, to comply with the food safety standards is promoting the applications of articulated robots in food production [155].

3) DELTA ROBOT

Delta robots or parallel-link manipulators have a layout configuration consisting of three to six arms, connected to a universal base with several rotational joints [147], creating a mechanism which makes it look spider-like. Delta robots have a hemispherical or a truncated conical work envelope (which is more restrictive than articulated robots); their lightweight links and individualized parallel arm placement, result in reduced inertia and load on the individual motors enabling very fast motion and reduced vibrations [156]. They are also renowned for their accuracy, and are predominantly used in industries where speed, efficiency and precision are paramount. This enables the high frequency handling of a large volume of products, making them a perfect choice for the food industry. Moreover they are suitable for other industries as well including (but not restricted to) the electronics and pharmaceutical industry. In primary food processing, delta robots are increasing in popularity with the prevalence of hygienic manipulator options [157], they are utilized for mainly for sorting and packaging applications.

4) CARTESIAN ROBOT

Cartesian robot or gantry robot features a configuration based on three orthogonal and linear axes. They have a work envelope similar to that of a rectangular prism or cuboid shape, enabling these manipulators to have easier planning and control. They have high payload capabilities and high accuracy, while being the cheapest type of robots in the market owing to their limited flexibility [147]. These features and their robust configuration enable them to effectively carry heavy loads, efficiently and accurately. Furthermore, their ease of maintenance and clean-ability, meets the hygiene requirements of the food industry to perform pick and place tasks and storage/retrieval operations [158] Moreover they find application in the electronics, automotive and 3D printing industries as well.

The aforementioned manipulator configurations are represented in Fig. 10

5) COBOTS

Cobots are collaborative robots designed to work safely with humans, sharing their work envelope. They have grown in popularity during the last few years, with increasing applications across several industries [19].

Cobots have certain advantages over traditional industrial robots in primary food handling, specially tailored suitability for SMEs. They feature user-friendly interfaces, obviating the need for specialized robotics engineers or programmers to manage basic applications, aligning well with SMEs [163], which often lack highly skilled personnel. Additionally, cobots require comparatively simple installation procedures, as they typically do not require the traditionally extensive safety measures required by industrial robots. Their protective systems and slower operational speeds enable safe collaboration with human operators in shared workspaces, while their design facilitates the repetitive handling of lighter loads, reducing ergonomic risks commonly associated with primary food handling. Cobots also boast a smaller installation footprint compared to their industrial counterparts, optimizing space utilization in food handling facilities. Moreover, leading cobot brands like Universal Robots offer compatible equipment and software solutions from external providers, streamlining device integration through the cobot's Human-Machine Interface (HMI) and enhancing operational efficiency and versatility. Cobots cannot directly replace workers' positions [164]. The production system should be adapted to integrate cobots correctly with human-robot collaboration. Factors such as ergonomics, safety, layout, and the study of operations easily carried out by cobots must be considered in the evaluation.

The previously discussed manipulator configurations are succinctly represented in Table 5, with salient points

FIGURE 10. Examples of the various robot configurations utilized in the food industry. (From left to right) articulated robot [159], cartesian robot [160], delta robot [161], and SCARA [162].

TABLE 5. A brief comparison of manipulator hardware configurations.

Hardware Equipment	Features	Pros	Cons
SCARA	• Specialized in vertical planar motions • Lobed hollow cylindrical work envelope • Compact footprint optimizes space utilization	• High Precision and Speed • Vertical manipulation capabilities • Hygienic Options	• Limited reach and range of motion • Payload limitations • Limited versatility
Articulated robot	• Multi-jointed arm for precise and versatile movement • High DOF enhancing flexibility and complex movement • Spherical or hemi-spherical work envelope • Versatile in diverse food processing operations	• Highly versatile applications • High flexibility, reach and payload variants • High level of control and precison • Hygienic Options	• Programming complexity • Longer setup and integration time
Delta robot	• Lightweight, parallel-arm structure • Hemispherical or trunctated cone work envelope • Suitable for high-frequency pick and place tasks • Optimal for hygienic work environments	• Exceptional speed and accuracy • Minimal footprint • Gentle product handling • Many hygienic options	• Limited reach and payload • Vibration at high speeds • Limited versatility
Cartesian robot	• Linear movement along orthogonal axes • Cuboidal work evelope • High levels of precision and repeatability • Efficient for stacking and palletizing operations	• Ideal for structured environments and is scalable • Cost effective • Easy integration	• Limited versatility • Speed limitations • Larger foot print
Cobot	• Multi-jointed arm for precise and versatile movement • High DOF enhancing flexibility and complex movement • Spherical or hemi-spherical work envelope • Versatile in diverse food processing operations	• Possibility to share work envelope with operators • High flexibility • High level of control and precission • Easyly programming and integration	• Limited load • Speed limitations • Larger foot print

highlighting their features, pros, and cons. Additionally, a representation of the advances in robotic technologies and available commercial robot-based solutions across the various food categories, are depicted in Table 6 to provide an overview of the state of research - highlighting the difficulty to materialize into market ready solutions. However, the availability of robots capable of being used in food processing (using food grade material, hygienic design, wash down capability, temperature resistance, etc.) is on the rise. The options are so numerous it is not feasible to list and evaluate individual robot models, even if we just consider the major robot manufacturers. The Fig. 11 is a subjective rating of the various robot configurations, and how they compare with each other, based on the available performance parameters cataloged on the website of the major robot manufacturers [157], [165], [166], [167], [168] .

TABLE 6. Robotic technologies in primary processing of food.

Food Category	Product	Relevant Product Features Considered	Process	Technology	Research	Commercialized
Dairy product	Bovine (cow) Milk	Color, viscosity, sugar and acidity	AMS (Automatic Milking System)	Harvesting	[169]	[170]
Vegetables	stems (Leeks)	Texture, color, firmness, physical state	Robotic cutting, cleaning and binding	Robotic primary processing	[138]	N/A
Nuts	walnuts	product integrity, presence of shell		InGaAs	[171]	N/A
Meat product	Beef (beef)	Color, density, dimensions, muscle-fat distribution, bone position	Butchering beef ribs	Robotic cutting	[142]	[172]
Meat product	Pork (pigs)	Color, density, dimensions, muscle-fat distribution	Pork belly trimming	Robotic water jet cutting	[142]	N/A
Meat product	Pork (pigs)	Color, density, dimensions, muscle-fat distribution	Robotic cutting with smart knife	Robotic primary processing	[173]	N/A
Fish and Seafood	Fish (Salmon)	Belly fat, Back fat, belly membrane, tail, blood clots	Robotic post trimming	Robotic cutting	[174]	N/A
Fish and Seafood	Fish (Rainbow trout and Salmon)	Head, tail, gills	Slaughtering, gutting and cleaning	Robotic primary processing	[132]	N/A
Meat product	Poultry (chicken)	Meat and fat composition, dimensions, bone placement	Deboning	Robotic primary processing	[175]	N/A

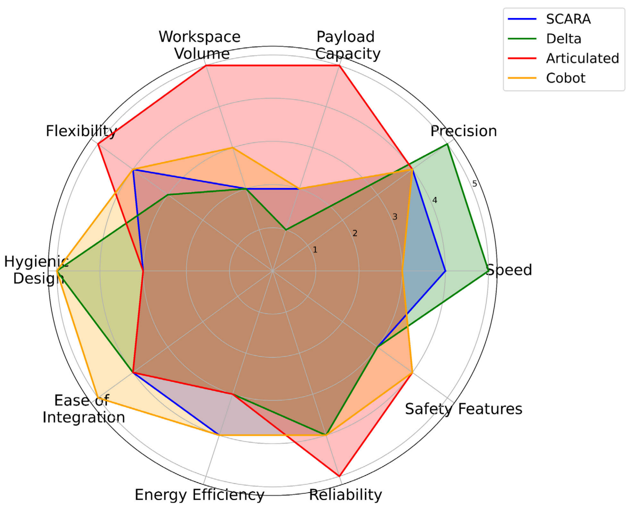

FIGURE 11. Graphical representation based on a relative analysis of the performance capabilities of various types of food processing robots, from the biggest robot manufacturers, compared across common parameters [157], [165], [166], [167], [168].

B. END-EFFECTOR

Handling is the main application of industrial robot installations carried out [19], and the pick and place process is the most common operation. The robot end-effector must be able to quickly grip the product, perform the 'pick' operation, provide a firm grip to prevent the product from being ejected or displaced during the movement between pick and place, and release the product rapidly with precision in position and orientation that the system requires (place operation).

Robot manipulation systems can be classified according to their grasp, hold, and manipulation capabilities. The grasping capability goes from the simplest, gripping the product in a predefined position and orientation, to increasing the system's complexity to handle products with large dimensional and shape tolerances, and finally, being able to manipulate products with unknown positions and orientations. The ability to hold a product varies from the simplest scenario, with no external disturbances, to the most complex scenario, where the manipulation system dynamically adapts to the object's characteristics and system disturbances (accelerations, impacts, product deformation). The manipulation capability goes from predefined and previously known positions to being able to manipulate by achieving the position and orientation of the product, even when the object is unknown, and the system itself can deduce its properties.

There are various technologies to choose from when creating or selecting end-effectors for robots. The two significant systems commonly used in the industry are astrictive and contact systems, each with advantages and disadvantages. Astrictive systems often use air in both suction and over-pressure.

Air suction with suction cups is a popular choice; it allows for product manipulation through pressure difference, is quick to act, is lightweight, and can be adapted to various shapes and height tolerances. However, they have limitations, such as malfunctioning on irregular or dirty surfaces, difficulty handling porous products, low shear forces limiting lateral accelerations in pick and place processes, and high energy consumption; they also risk damaging the product and its surface. Understanding these pros and cons is crucial for making the right choice for automation needs. When handling high-volume and heavy products, a practical solution is to use multiple suction cups on a single manipulation system. The force exerted on the product surface depends on the generated vacuum and the surface area of the suction cup. In heavy or large products is necessary the use of several suction cups, for these cases, it is essential to consider using independent vacuum systems and/or cutoff valves. These can help limit the maximum airflow when the suction cup does not seal tightly against the product, ensuring efficient and effective handling. In complex shapes products, suction cups must be distributed along the product to adapt to its shape. 3D printing systems can facilitate manufacturing multi-suction cup end-effectors with complex shapes and reduced weights, increasing the adaptability and versatility of robotic systems.

Blowing allows product manipulation by generating the Bernoulli effect when a high-speed air stream over the product surface creates a depression over the product that can be used to manipulate it. These systems enable contactless product handling and are simple and robust, with forces distributed over a wide surface area, making them suitable for light, flat, and fragile products. This system does not transmit shear forces, so it is necessary to incorporate stops to prevent the product from being released during translation.

Contact manipulation or gripping systems are widely used in robotic manipulation. These systems can be classified according to the number of fingers, the range of finger motion, the type of motion (angular or parallel), the type of actuator used (usually pneumatic or electric), the closing force, and the shape of the fingers. Pneumatic actuators are very easy to control, have a good weight-force-speed ratio, do not suffer from mechanical blocking issues, and are easier to control than electric actuators; however, they do not allow for position control. Contact manipulation requires that the lateral surfaces where pressure is applied to the product be cleared during pick operation and place operation.

Parallel grippers ensure the same finger force regardless of the position of the fingers. Require robust linear guides (friction or ball screws) for handling high loads or long fingers, limiting their range of motion. Fingers operate perpendicular to the product and can adapt to its shape. They offer superior grip precision, irrespective of object size. In angular grippers, fingers pivot at a short angle, offering internal mechanical simplicity and durability compared to parallel grippers. The finger angle varies depending on the size of the object. In radial grippers, fingers pivot at a large angle, providing workspace flexibility and collision avoidance during the robot approach but requiring higher object clearance.

Adapting grippers or end-effectors to accommodate a variety of shapes and sizes is a difficult task not solved for all cases. In many cases, automation processes in primary packaging are designed for manual operation. The manual operation process cannot be directly translated into a robot process due to special restrictions in robot automation, particularly for robot grippers.

1) END-EFFECTORS FOR FOOD

For a proper selection of the robotic gripper for primary food handling, it is necessary to analyze the product and its characteristics, considering its properties and arrangement within the process. Understanding the product properties is the foundation of any handling system. Typically, not all information is available in advance, and it is necessary to investigate its characteristics and tolerances, including maximum and minimum dimensions, shapes, potential grasping areas, location of the center of mass, and maximum pressure not to damage the products. It is necessary to study the process to be carried out with the product, including the sequence of movements, position accuracy, accessibility to the product, and the distribution of various elements such as conveyors or auxiliary systems. It is crucial to consider the distribution of the product in the process to facilitate the design of the robot end-effector. Significant modifications are often required to simplify and make the handling system feasible. Fig. 12 summarizes the most significant steps for the selection and/or design of a robot end-effector.

In the industry, the preferred parameter is to go as fast as possible to achieve the shortest cycle time, thereby optimizing the economic performance of the installation. Meeting speed requirements is challenging when the object's properties are not fully defined or vary over time, as in primary food handling. Adapting the handling system to various shapes and sizes involves using end-effectors with wider motion ranges, which are heavier and, therefore, more challenging to achieve a reduced cycle time. The ultimate solution is a compromise among various requirements, where the entire set of equipment used, their distribution, the robot, and the handling system must be considered. Simple solutions are generally those that achieve a reduction in requirements, lower costs, and simplify processes.

There is a growing interest in developing new end-effectors for robots. Pneumatic end-effectors are advancing towards new, more flexible systems thanks to 3D manufacturing techniques, modular systems suitable for collaborative robots, and new materials. These new features can facilitate food manipulation [177].

Different challenges limit finding effective end-effectors for robot primary food handling [178]. They face many difficulties, such as softness, fragility, irregular shapes, wetness, slipperiness, sticky surfaces, and hygienic requirements. End-effectors must have simple motion, hygienic design, high-speed operation, and low cost. End-effectors are plenty of opportunities for robotic end-effectors due to an aging society and labor shortages. Soft robotics end-effectors have increased recently, but only some user cases have been reported. The high mix and low volume are the most significant difficulties in the food industry.

Current robot end-effector designs have been studied considering their mechanism, degrees of freedom, and grasping capabilities [179]. End-effectors with compliant mechanisms, with three or more phalanges, are adequate for complex shapes. Constrained mechanisms with rigid links are good for heavy objects, but their motion range is limited. Underconstrained mechanisms with rigid links are adequate to undefined shape objects exerting high forces, but their design limits their range of motion and increases the mechanical complexity. Academic researchers have been focused on developing underconstrained mechanisms and

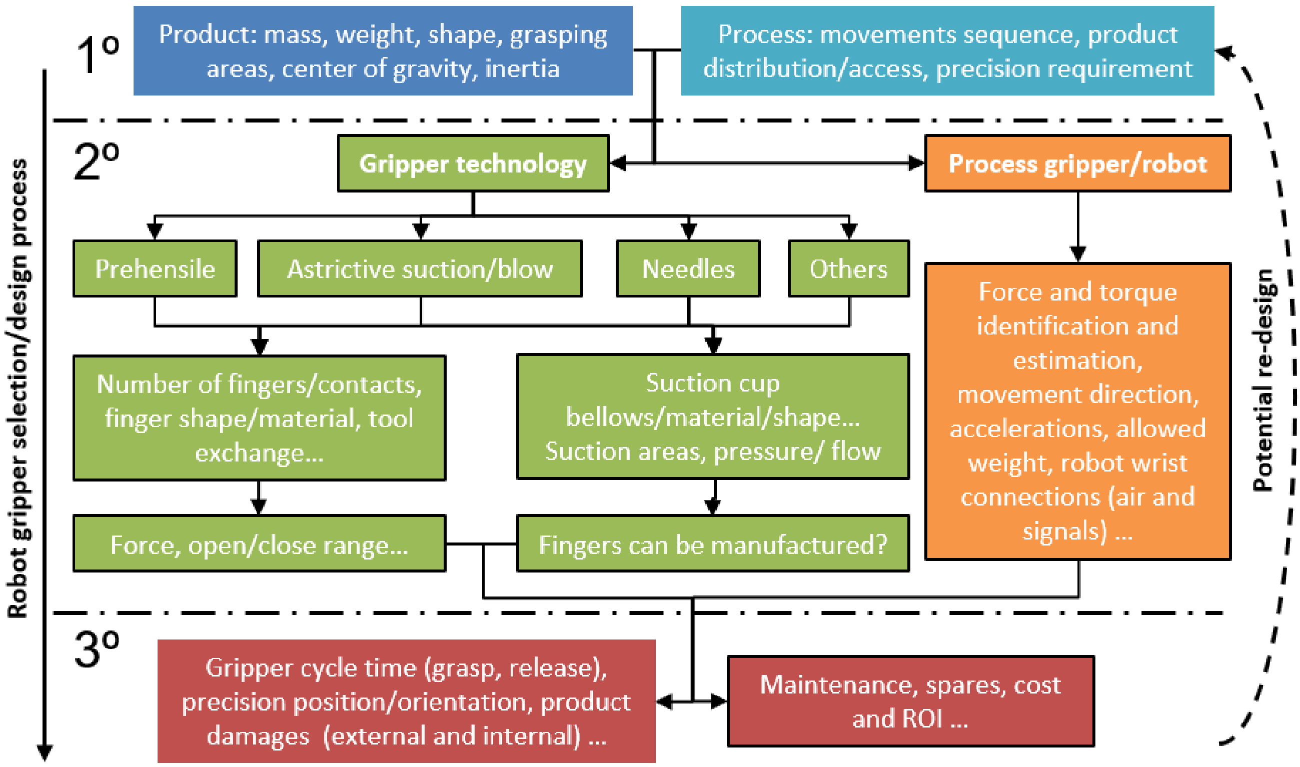

FIGURE 12. Flowchart for robot gripper selection and design process. Begin by thoroughly studying the product and its associated manufacturing process. Next, based on the insights gained from the initial study, choose the appropriate gripper technology (astrictive [176]) and determine the optimal robot/gripper process. Proceed to assembly and commissioning, where the behavior of the gripper is carefully checked. Simultaneously, optimize the robot process, taking into account any necessary adjustments or potential re-designs.

actuators. The authors consider passive-compliant mechanisms with rigid links and gecko-inspire surfaces the best for handling objects with different shapes and weights. They have a balance between flexibility and strength. If accurate grasping forces are requested, constrained mechanisms with rigid links are the best. No position and control forces have been achieved with compliant links with underconstrained mechanisms, but the ability to manipulate different shapes increases.

In agriculture, there is prominent research on soft robotics end-effectors [180]; they look for improved flexibility, safety, accuracy, and adaptability. Soft robotics is a promising solution to the challenges of harvesting and handling agricultural products. They have gentle behavior but should advance in control, sensors, grasping evaluation, reliability, standardization, materials, and mechanical design [181]. Harvesting requires much low-skilled labor working in an unfriendly environment. Harvesting involves grip and detachment, where many simple operations should be considered, such as cutting, pulling, bending, twisting, or combinations. Current soft end-effectors' performance does not fill harvesting labor gaps; maybe soft end-effectors that combine simple operations could cover their needs. Most of the soft end-effectors have only been tested for a few samples and only a specific crop. Soft end-effectors need design standardization [182]. Despite potential advances in using soft robotics end-effectors, the most popular end-effectors are multi-finger contact grippers alone or combined with scissors or saw [183].

End-effectors have the opportunity to sense products while touching them. Tactile sensing in agri-food manipulation has a potential interest in robotic harvesting (ripeness, quality, pest control, etc.), primary packaging and handling (gentle manipulation and quality control), and kitchen robots (control systems). Current tactile sensors need to increase sensitive areas, improve dynamic ranges, increase resolution, and develop commercial calibration systems. In the industry, the inherent complexity of agri-food products limits the use of the complex tactile sensors developed [184].

Much automation of product lines for packaging fresh products has been done according to human handling. These lines are a good opportunity for robotics, but many challenges remain for robot manipulation should be developed to replace human handling. Soft robotics end-effectors are an opportunity solution, but their main limitations are lack of motion control, tactile sensors, dexterity, and still high investment in robotics [185].

The variability in shapes, dimensions, and sensibility of agri-food products makes it necessary to find handling systems capable of meeting these requirements. The 3D printing manufacturing of soft robotics end-effectors presents a clear opportunity [186] in this market because:

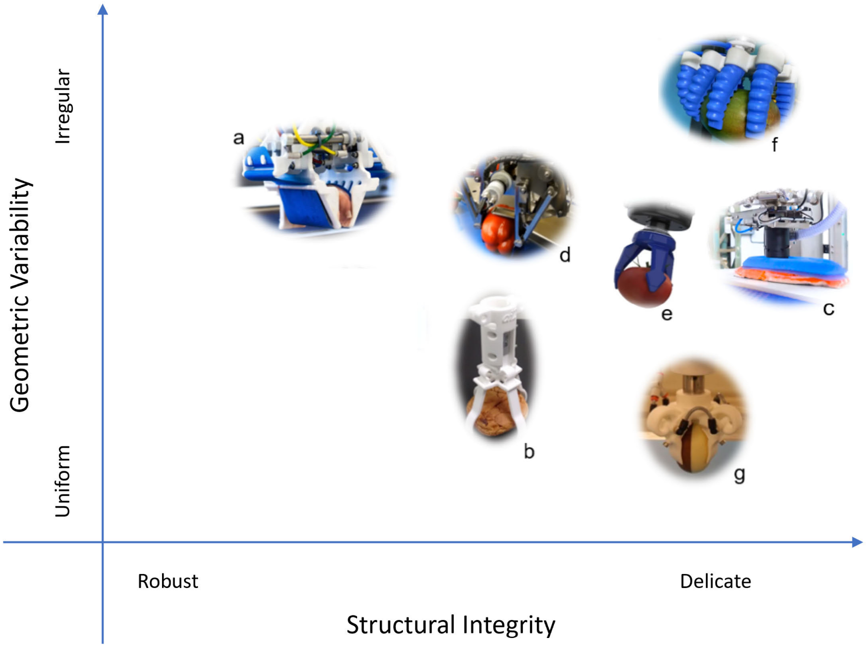

FIGURE 13. Examples of end-effectors in robotic primary food packaging: a) RobotBacher flex 3D printed self-centering enclosing gripper for poultry from Marel [188], b) compliant 4 fingers 3D printed in FDA polyamide gripper with SLS printing technology from automatics and industrial informatics research institute [189], c) Suction cup gripper for salmon handling from Gripwiq [190], d) Underactuated mechanical gripper from Lacquey [191], e) piSoftgrip for fruits vacuum-based soft grip from Piab [192], f) Soft gripper fingers for the industry from SoftGripping GmbH made it in food-grade silicone [193], g) A single piece of three-finger 3D printed gripper made it in Polyamide [187].

- It is a quick way to find soft end-effectors customized for specific features and applications.
- Reduce manufacturing complexity.
- Short implementation times.
- Provide an easy way for design iterations.
- Provide the ability to manufacture parts that cannot be made with conventional manufacturing techniques [187].
- Open the possibility of using various materials and integrating sensors.

The current major issues of 3D printing manufacturing are different methodologies, materials, resolution, reliability, and repeatability. Despite that, different manufacturers have made straightforward advances using 3D printing technology to implement end-effectors in robotic primary packaging Fig. 13. When the dimensions are highly irregular, increasing the finger aperture range Fig. 13a is necessary. If the product cannot tolerate high suction forces, the area can be increased with suction cups covering a large portion of the product surface Fig. 13c. It is necessary to find the optimal geometry that adapts to each product. Various technologies have been employed to achieve this. Infra-actuated mechanisms consist of rigid solids and joints that have more degrees of freedom than the number of actuators. Each of the solids is locked upon contact with the product. Usually, there will be as many contact points as rigid solids and infra-actuated degrees of freedom the end-effector mechanism has. The main drawbacks are the lack of trajectory control and difficulties finding mechanisms that lock as needed to grasp the product. Some examples in the market are in Fig. 13d. The alternative to rigid solids is to use flexible materials in the end-effector's fingers that adapt to the shape of the products to improve this contact and limit high-pressure contact points. It is necessary to increase the number of contact surfaces, reduce contact rigidity, use independent and self-adaptable actuators for each finger Fig. 13e, and reduce weight to avoid inertial efforts due to high-speed movements. 3D printing allows for designs in a single piece an end-effector with multiple independent fingers Fig. 13b with pneumatic actuators Fig. 13g. Very soft materials such as silicone can design movements that mimic human finger movements, thus allowing for enormous adaptability to various shapes Fig. 13f.

After analyzing grippers currently used in the industry for primary food handling, it is possible to deduce the general properties of the different systems employed, summarized in Fig. 14. In these industrial designs, design modifications, adaptations to specific products or processes, or new materials can significantly change the main characteristics shown in the Fig. 14.

C. LOGISTICS

Material handling and transportation are two essential components in the world of logistics and supply chain management, especially in the context of primary food processing.

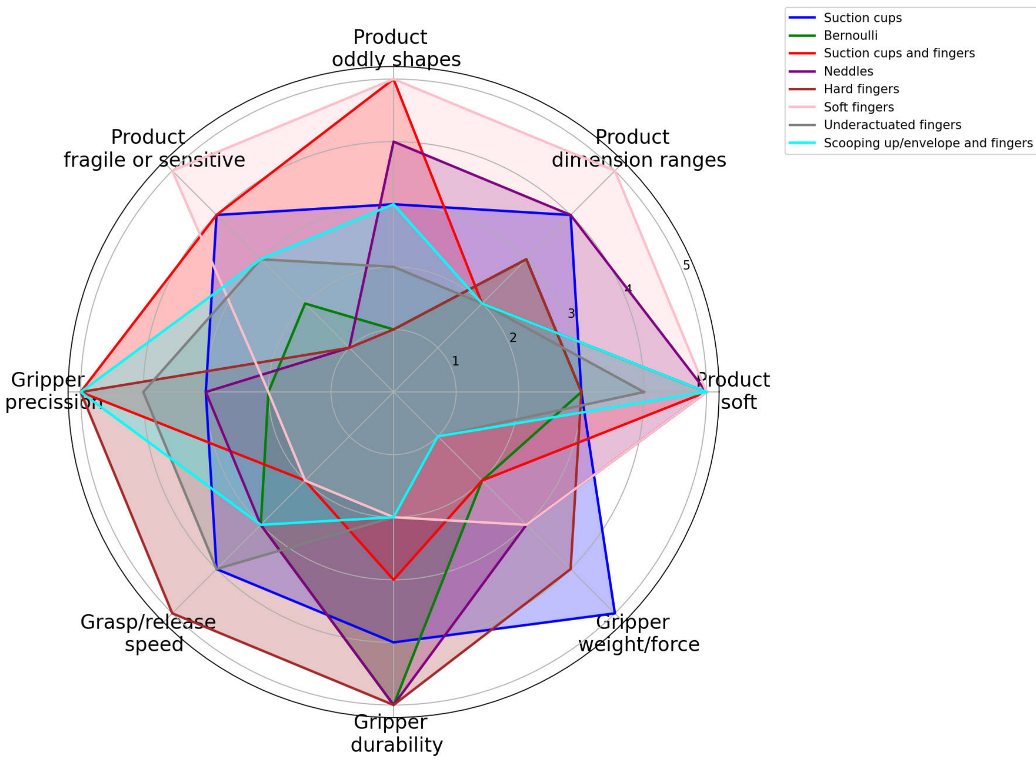

FIGURE 14. Overall comparison of robot gripper features for primary handling in the food industry.

- Material handling involves the art and science of moving, packaging, storing of substances in any form [194]. It primarily deals with the efficient handling of materials within a predefined area, such as a production facility. This includes the use of equipment like conveyors, elevators, pumps, and cranes.
- Transportation, on the other hand, is the process of physically moving products between different geographical locations. It plays a role at various stages of product completion and involves the use of trucks, rail, ships, and airways for moving products across large distances.

While material handling and transportation may appear analogous as they both involve product movement, they fulfill unique roles within the supply chain. Material handling focuses on the internal management of materials, while transportation is responsible for the external movement of products. However, to avoid confusion in the terminology of material handling- typically referring to moving products within a facility, and material handling-involving robotic manipulation (such as pick and place), we will refer to material handling as 'transportation' in the remainder of the paper. In this section, we will delve into the transportation (material handling) principles of food processing and highlight advancements in related technologies.

Transportation especially in food production, is a key area of focus primarily due to the fragile nature and biological material property of food. If the working environment or equipment is not maintained in the optimal conditions or predefined sanitary standards, this can cause rapid decrease in the quality of the food product, due to decay or disease. In order to prevent the deterioration in the quality of the food products, the equipment hardware which comes into direct contact with the product must be constructed with materials which are resistant to corrosion, which can also be easily cleaned [195]. Some of the guidelines which can greatly improve the efficiency of transportation in production processes are as follows:

- Consolidate the product movement and handle it in bulk.
- Automating the process wherever applicable.
- Employ gravity to act as a primary mover of product whenever possible and utilize all the layers of the building.
- Avoid unnecessary product movement and optimize the processing plant layout to minimize movement and place related activity and operation zones near each other.
- Combine operations to eliminate the handling between them [196].

Different transportation approaches are used based on the physical property of the respective food product. One of the biggest factors determining the nature of the equipment to perform the local transportation, is the consistency and structural integrity of the food product. Based on the medium (nature) of transportation, you could broadly classify conveyors into mechanical conveyors, fluid conveyors, and monorails. However these are broad-stroke categories and there are numerous sub-types for each of them. Some additional details regarding the various conveyor types are as follows:

1) MECHANICAL CONVEYORS

Mechanical conveyors are systems designed to transport bulk materials or goods using mechanical mechanisms like belts, screws, or rollers. They facilitate the movement of materials along predetermined paths within industrial settings for efficient handling and processing. Belt Conveyors have long been the backbone of production operations, since they were popularized in the mass production assembly lines of the Ford Motor Company [197]. In the context of food production, their capabilities for transporting bulk food products which are generally non-abrasive, transport stable, uniform size and shape, and non- reactive, are unparalleled. The most bare bones construction of a belt conveyor entails a seamless belt, which is maintained under tension between two or more rollers (where at least one of them acts as the driver). However, an issue particular to the food sector would be the emphasis placed on the material of the belt, which comes in direct contact with the food. The belt can be made of homogeneous or composite materials, including fabrics, plastics, and metals. Each material offers unique characteristics, depending on the application, environmental factors, cleaning requirements, and food-specific properties [196].

Based on the nature of belting there are several categories for distinguishing between the various types of belt conveyors. They are:

- *Homogeneous flat belts* are manufactured from a single extrusion of thermoplastic elastomer. This belt possesses the required physical and material properties, making it safe for coming into direct contact with food during primary processing. The tops of the belt can either be smooth or textured. Butt welding the material is the preferred method for sealing the belt, and creating a completely flush seam.
- *Fabric-reinforced belts* are manufactured by incorporating a reinforcing fabric/carcass layer sandwiched in between thermoplastic or rubber surfaces. Ply belts are comparatively inexpensive, and can be smooth on the top or textured. These belts are made continuous/endless by means of press welding, temporary mechanical fasteners can also be used. However, they are generally considered unsanitary for food safe belts [198].
- *Positive-Drive homogeneous belts* do not operate with the traditional friction rollers. On the contrary the drive is transferred to the belts by means of an array of teeth on its under side, and these teeth engage with a sprocket wheel or a toothed drive attached to a rotary motor. The teeth element could be extruded from the belt material during production, making it an integral part of the belt. Or they could be welded to the underside of an already extruded flat belt. They are usually made of homogeneous food safe material, which eliminates the risk of exposure of unsafe reinforcement material, while also avoiding the use of temporary fasteners and face similar issues as that of ply belts. As they are positively driven (strong link between belt and drive), they can handle significant loads.
- *Modular belts* are typically plastic belts consisting of modules, in the form of platelets which are connected and held together by pins. These belts are positively driven by means of a toothed underside which engages to a sprocket wheel or toothed drive or a low tension drum motor drive. Modular belts are renown for their minumum friction, high strength and a high resistance to corrosion, abrasion, and cleaning agents. Additionally, they are well suited for systems requiring complex curves in converging and diverging production lines. However it is possible that creep and material fatigue, with constant exposure to extreme temperatures, abrasive food particles, and chemical elements present in food could comprimise the aforementioned physical capabilities.
- *Wire and Metal belts* consist of metal wires which are woven together from individual strands. They have open structures which can allow air and fluids to flow through the belt. These belts can convey the products along straight lines and through curves along varying elevation levels, and can be operated at high temperatures ranging between 150 ° C to 800 ° C. The design of the individual cable strands are made in the form of loops, which are interconnected with joining clips or splice strands.
- *Round and V-profile belts* are typically utilised to transfer light weight objects. The shape of the profile enables a strong tension and minimal contact with the product being conveyed. They are utilized for food coating, and for spreading or separating the product, and are often used in packaging applications. The materials utilized for producing these belts are homogeneous, avoiding the hassles posed by the ply belt types [199].

The Fig. 15 is a representation of the various types of mechanical conveyors utilized in the food industry.

2) VIBRATORY CONVEYORS

Vibratory conveyors propagate their payload, which (in the food sector) primarily consists of bulk solids and granular material, by repeatedly displacing them over small distances. The payload material can either slide along or be momentarily thrown forward from the surface of the conveyor deck, with each displacing stroke. The mechanism which promotes the flow of materials along the conveyor deck is through sinusoidal vibrations [205]. However, depending on the application and nature of the prime mover, different vibration patterns could be achieved. The linear vibration pattern is the most suitable for transporting solid food products, additionally, it also does not require the utilization of gravity to move the product along the deck (although it does have a significant impact on the performance) [206].

Vibratory conveyors are capable of performing additional operations on the transferred product, some of these

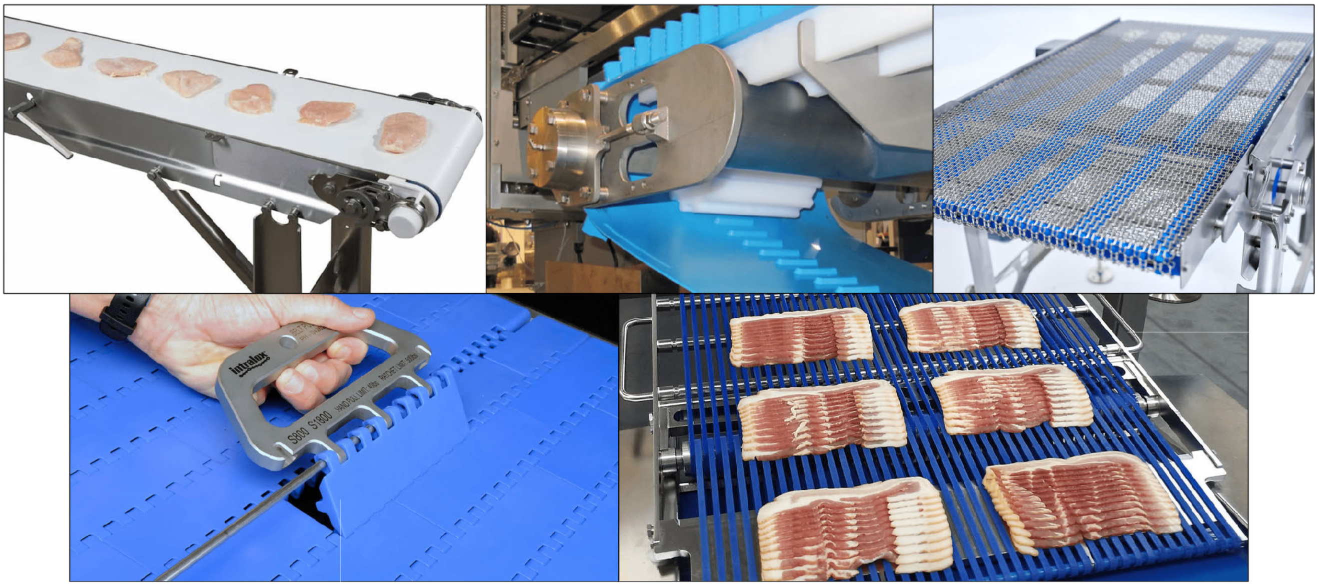

FIGURE 15. Examples of the various mechanical conveyors utilized in the food industry. Row 1: (From left to right) homogeneous flat-belt conveyor [200], positive-drive homogeneous belts [201], and wire and metal belts [202]. Row 2: (From left to right) modular belts [203], and Round belts [204].

operations which are relevant for the food industry are as follows: Slicing is the process wherein conveyed objects could be sorted into groups based on their graded size; Scalping is the process of selectively retaining and processing a single size (or group of sizes), while excluding all others for further examination or screening. De-dusting as the name suggests is the removal of dust and/or unwanted fine particles, that may be generated during storage or handling [23]. Pasteurization by thermally processing the product, as it moves along the production process, by using a continuous vibrating conveyor system with resistive heating [207]. Chilling the product, to reduce microbial growth and enzymatic reactions, is possible increasing the dwell time on the conveyor or by circulating cold refrigerants along the conveyor walls [208].

3) SCREW CONVEYORS

Screw conveyors typically contain a helical Screw-shaft rotating inside a hollowed out trough or cylinder. They are used to transfer bulk solids, which includes fine food particles (flour, sugar, etc.) and small particulate foods (peas and grains) [209]. Additionally, they are also utilized for mixing ingredients, and for performing loading and unloading operations. These conveyor systems are known for their high throughput control, while maintaining a high efficiency with low operating and maintenance costs [210]. As these conveyors are enclosed structures, they could work in hazardous environments and consecutively, they generate very minimal dust and material loss, making them a profitable and an environmentally viable option. The material being conveyed is designed to be transported in the bottom side of the trough, and as the conveyor is enclosed the orientation of transportation could either be horizontal, vertical or inclined depending the application and the product conveyed [211]. However, due to power consumption restraints, the dimension of a screw conveyor is restricted to less than 30 m [211], [212].

4) FLUID CONVEYORS

Conveyor systems which utilize a fluid as the main operating medium for conveyance, can be either classified as a pneumatic conveyor (if the operating medium is a compressible fluid/air/vacuum) or hydraulic conveyor (if the operating medium is a non-compressible fluid/oil/water).

Pneumatic conveyors are versatile systems and are suitable for handling a wide array of materials, such as powders, granules and bulk solids. Compressed dry air or vacuum is generally the conveying medium of choice for most food products [211]. Depending on the nature of the application- the produce could be conveyed in suspension mode (low quantity of product is moved with a higher proportion of fluid), and it is termed as dilute phase; in non-suspension mode (high quantity of product is moved with a lower proportion of fluid), which is termed as dense phase. The fluid speed for suspension mode conveyance ranges between 20 m/s to 40 m/s, while for the non-suspension mode it ranges between 1 m/s to 3 m/s [213]. Solid loading ratio *(Φ)* is a dimensionless number [214], which provides the rating capacity for any pneumatic conveying system, and it is defined by (1):

$$\Phi = \dot{m}_p/\dot{m}_a \tag{1}$$

where, $\dot{m}_p$ is the mass flow rate of the material conveyed (kg/h) and $\dot{m}_a$ is the mass flow rate of the fluid medium (kg/h) used for conveying [214]. The solid loading ratio for dilute phase remains under 15, whereas, for the dense phase it could go as high as 100 [215].

TABLE 7. A brief comparison of transportation hardware.

Hardware Equipment	Features	Pros	Cons
Mechanical Conveyors	• Supports multiple speed and load capacities • Configurable to various food processing layouts • Compliant with food safety and hygiene standards • Facilitates gentle handling to preserve food quality	• Cost effective • Continuos operation • Diverse configurations • Hygienic design	• Space requirements • Cannot convey bulk and particulate product
Vibratory Conveyors	• Suitable for conveying bulk and particulate product • Simple construction and comparitively lesser moving parts • Available in a range of capacities and flow rates • Versatile secondary operations in addition to conveyance	• Handles hot and abrasive materials • Efficient sorting and separation • Customizable for specific processes • Hygienic Options	• Noise levels • Wear and tear • Conveying length and orientation
Screw Conveyors	• Suitable for conveying bulk and particulate product • Capable of horizontal, vertical, inclined conveyance • Allows controlled flow rates • Enables controlled and efficient ingredient feeding and mixing.	• High versatility regarding product types conveyed • Relatively low operation and maintenance cost • Continuous flow and operation • Enclosed system promotes safety and cleanliness	• Challenging to clean • Wear and tear • Unsuitable for fragile and sticky products
Fluid Conveyor	• Suitable for conveying bulk and particulate product • Allows precise control over flow rates and volumes • Compatible with temperature-controlled processes • Maintains integrity and quality of food products	• High versatility regarding product types conveyed • Enclosed system promotes safety and cleanliness • Hygienic designs available	• Cleaning and sanitation • Maintenance requirements • Wear and tear
Monorail	• Easy-to-clean surfaces for maintaining food safety standards. • Transportation above processing area, minimizing floor traffic • Suitable for cold and refrigerated environments • Suitable for linear or curved path transport	• Efficient space utilization • Minimal coss contamination • Easy cleanability and maintenance	• Limited versatility in product type • Complexity in initial integration

Pneumatic conveyors with a hygienic design, proper sanitary sealing and connections [135], and with regulated compressed air quality are in prevalent use for transporting granular and bulk products.

5) MONORAIL

Monorail systems predominantly serve as a pivotal means of product transportation within various industrial contexts, particularly in the logistical transfer of goods from warehousing facilities to production and processing areas [216]. These systems functionally resemble mechanical conveyors, wherein the transportation of objects is facilitated through a physical support structure driven by an electric prime-mover. This enables monorail systems to efficiently and autonomously transport products along their dedicated rail infrastructure with high levels of effectiveness. In contemporary industrial settings, the deployment of monorail systems finds extensive application, with a significant presence in sectors such as meat processing, where they play a crucial role in the physical handling/transportation of a majority of livestock [217]. They prominently feature in the physical transportation and precise measurement of animal carcass weights at various stages of processing (which ranges from post slaughter bleeding, hide and head removal, evisceration, splitting, trimming, washing and storage). Moreover, the utility of monorail systems transcends the meat industry, extending to sectors encompassing beverages, tea, and baking.

FIGURE 16. Examples of other types of conveyors utilized in the food industry. Row 1: (From left to right) vibratory conveyor [218], Pneumatic (fluid) conveyor [219]. Row 2: (From left to right) monorails for animal carcasses [220], screw conveyor [221].

The Fig. 16 is a representation of the various types of mechanical conveyors utilized in the food industry. The aforementioned conveyor types are succinctly represented in Table 7, with salient points highlighting their features, pros and cons. Furthermore, a representation of the advances in conveying technologies and available commercial products across the various food categories is depicted in Table 8 to provide an overview of available research and solutions.

TABLE 8. Transportation technologies in primary processing of food.

Food Category	Product	Relevant Product Features Considered	Secondary Processes	Technology	Research	Commercialized
Meat Product	Carcasses (Cattle, goat, sheep, pig, etc.)	Varying size, whole cuts	Bleeding/ skinning/ Evisceration/ Splitting	Monorail	[217]	[220]
Fruits and Vegetables	Citrus fruits, tomatoes and sugar beets	Color, Firmness, sugar and acidity, shape	-	Mechanical elevators and conveyors	[222]	[223]
Fruits and Vegetables	Whole fruit, potatoes, carrots, beets.	Size, shape, surface integrity,	-	Hydraulic conveyors - Pumping (centrifugal pumps) and piping	[224]	[225]
Fish and Seafood	Fish, shrimp, prawns Carcasses, fillets, steaks	Color, size, whole body integrity, texture	-	Pumping (centrifugal pumps) and piping	[224]	[226]
Poultry product	Egg	Weight, colour, shape	Egg grading and separation	Conveyor	[227]	[228]
Vegetables	-	Size, shape, surface integrity,	Cleaning	Hydraulic conveyors	[217]	N/A
Fruits	Citrus fruits (Lemons, lime, oranges)	Size, shape, surface integrity, color	Cleaning/ pre-grading	Roller conveyors	[229]	[230]
Nuts	Oilseeds (Ground nut)	Density, specific gravity, Viscosity, Friction coeff.	Oil extraction	Screw pump	[231]	[232]
Nuts	Oilseeds (Mustard seeds, black peppers, soya beans)	Density, specific gravity, surface profile, Friction coeff.	Sorting/separation of bad seeds and impurities	Spiral separator/ upward conveyor	[227]	N/A
Seeds	Ground nut	Density, specific gravity, viscosity, Friction coeff.	Oil extraction	Screw pump	[231]	[232]
Seeds	Coffee beans and powder	Density, specific gravity, surface profile, friction coeff.	Coffee bean and coffee powder transportation	Pneumatic conveyor	[233]	[234], [235]

IV. SYSTEMS INTEGRATION AND CASE STUDIES

This section attempts to briefly bring together the various subsystem discussed earlier, from an integration point of view. Furthermore, this section would present a few relevant use cases from industrial applications of robotic and machine vision technologies, for the processing of food.

A. INTEGRATED SYSTEMS

According to the International Society of Automation (ISA), the standard for the integration of enterprise and control systems is ISA 95 [236]. It provides the framework which defines the communication and data hierarchies of the various automation devices, and their specific functions at each levels. Additionally, it also introduces a detailed information model, that specifies how the devices must communicate with each other- within and across the layers. The automation pyramid is diagrammatic representation of these hierarchies and information models, and can be seen in Fig. 17.

The devices such as robots, end-effectors, conveyors and machine vision cameras form the lowest layers (actuators and sensors), where the numbers of data points are high, but the size and complexity of the data generated is low. These low level device are controlled by PLCs (Programmable Logic Controller), micro controllers, etc., which form the next hierarchical layer. The supervision layer consisting of HMIs (Human Machine Interface)and SCADA (Supervisory Control and Data Acquisition) systems (sitting above the control layer), is where the status of production and machinery performance can be monitored and controlled with real-time human intervention/interaction [237]. These three layers form the base of the pyramid and is the framework used by most full scale automation setups, with some devices and systems blending between two layers, owing to them being multi-functional. The Manufacturing Operations management layer is the second highest layer on the pyramid and it mainly pertains to the Manufacturing Execution System (MES) of the company. The MES deals with production scheduling, inventory management, work order management, worker management, and process control. The top layer of the pyramid deals with Business Planning and Logistics which is handled by the Enterprise Resource Planning (ERP) module. The ERP deals with financial managment, supply chain management, human resources management, sales and order management, and production planning. The top two layers of the pyramid consists of the control systems which are critical for manufacturing and business management, while these are two distinct layers with their own functionalities, they are interdependent and often integrated to improve efficiency, operational reliability and decision making [238].

The systems and devices across the various layers of the automation pyramid require a reliable infrastructure to

TABLE 9. Relevant communication protocols for industry 4.0 and 5.0.

S.No	Protocol name	Data Rate	Determinism	Topology	Scalability	Reliability	Supported Devices	Supported Data types	Standardization	cost	Integration with IT	Vendor Support	Reference
1	CAN Bus	Upto 1 Mbps	High	Bus	Medium	High	Sensors, actuators	Discrete, Analog	ISO 11898	Low	Medium	Extensivie	[240]
2	ControlNet	5 Mbps	High	Bus	Medium	High	PLCs, I/O Modules	Discrete, Analog	IEC 61158/61784	Low	Medium	Extensivie	[240], [241]
3	DDS	Configurable, High	Medium	Peer-to-Peer	High	High	Distributed Systems, IoT Devices	Complex, Real-time	OMG Standard	Medium	High	Growing	[242]
4	DeviceNet	125 kbps - 500 kbps	Medium	Bus	Medium	High	Sensors, actuators	Discrete, Analog	Open	Low	Medium	Extensive	[240]
5	EtherCAT	1 Gbps	High	Line, Star	High	High	Sensors, actuators	Discrete, Analog	IEC 61158	Medium	High	Extensive	[243], [244]
6	EtherNet/IP	upto 100 Mbps	High	Star, Line	High	High	PLCs, Sensors	Discrete, Analog	IEC 61158/61784	High	High	Extensive	[240]
7	FOUNDATION fieldbus	31.25 Kbps	High	Bus, Ring	Medium	High	Field Devices, Controllers	Discrete, Analog, Complex	IEC 61158	Medium	Medium	Extensive	[245]
8	Interbus	500 Kbps	High	Ring, Star	Medium	High	PLCs, I/O Modules	Discrete, Analog	IEC 61158	Medium	Medium	Extensive	[246], [247]
9	IO-Link	230.4 Kbps	Medium	Point-to-Point	Medium	Medium	Sensors, Actuators	Discrete, Analog	IEC 61131-9	Low	Medium	Growing	[248], [249]
10	Modbus	1.2 kbps - 10 Mbps	Low	Line, Star	Medium	Medium	PLCs, Sensors	Discrete, Analog	IEC 61158	Low	Medium	Extensive	[250], [251]
11	MQTT	Variable	Low	Star	High	Medium	IoT Devices	Complex	Open	Low	High	Growing	[252], [253]
12	OPC UA	Upto 1 Gbps	Medium	Star, Mesh	High	High	Industrial IoT, MES	Complex, Real-time	IEC 62541	Medium	High	Extensive	[254], [255]
13	PROFINET	Upto 100 Mbps	High	Star, Line	High	High	PLCs, Sensors	Discrete, Analog	IEC 61158/61784	High	High	Extensive	[256], [257]
14	RS-232	20 kbps - 1 Mbps	Low	Point-to-Point	Low	Medium	Computers, Sensors	Discrete, Analog	EIA-232	Low	Low	Extensive	[258]
15	RS-485	Up to 10 Mbps	Medium	Bus, Multi-drop	Medium	Medium	Sensors, Actuators	Discrete, Analog	EIA-485	Low	Low	Extensive	[258]
16	TCP/IP	Up to 10 Gbps	Low	Star, Mesh	High	High	Computers, Routers	Complex, Any	IETF Standards	Medium	High	Extensive	[259], [260]
17	ZigBee	250 kbps (2.4 GHz)	Medium	Star, Mesh	High	Medium	Smart Meters, Sensors	Discrete, Analog	IEEE 802.15.4	Low	Medium	Growing	[261], [262]

communicate between each other. High speed communication and seamless integration is a cornerstone for Industry 4.0, that enterprises aim to achieve [239]. However, some technologies are suited better to certain applications, and automation engineers need to make tradeoffs to get the most suitable technology for their respective process application. An analysis of a selection of relevant protocols suitable for food automation industry, evaluated across common parameters are presented in Table 9.

B. CASE STUDIES

in this section, we showcase three different real scenarios in order to illustrate how machine vision and robotic systems are tailored according to the particular needs of the problem at hand.

1) CASE STUDY 1

The first use case regards Multiscan Technologies [263], which is a Spanish company specialized in vision systems developed for to agri-food industry. We describe a multi-view system that was implemented in collaboration with Fondazione Bruno Kessler, Trento-Italy, for grading orange fruits based on machine vision. The system aims at grading the oranges into three classes, namely good, bad, and undefined, based only on the external quality of the fruits.

The grading software is based on deep learning, which necessitates a training process by leveraging image and label examples. Therefore, a dataset was acquired by Multiscan Technologies. The dataset contains the images along with their grade annotations. To this end, the oranges go through a roller conveyor that moves them forward and rotates them simultaneously (See Fig. 18) to ensure that each orange is captured from different angles by the camera. As seen in Fig. 20, the good grade oranges show a clean skin, while the bad class oranges often manifest blemishes and bruises. The undefined class oranges, however, report imperfections that are neither too severe to be graded as bad nor insignificant to be considered good.

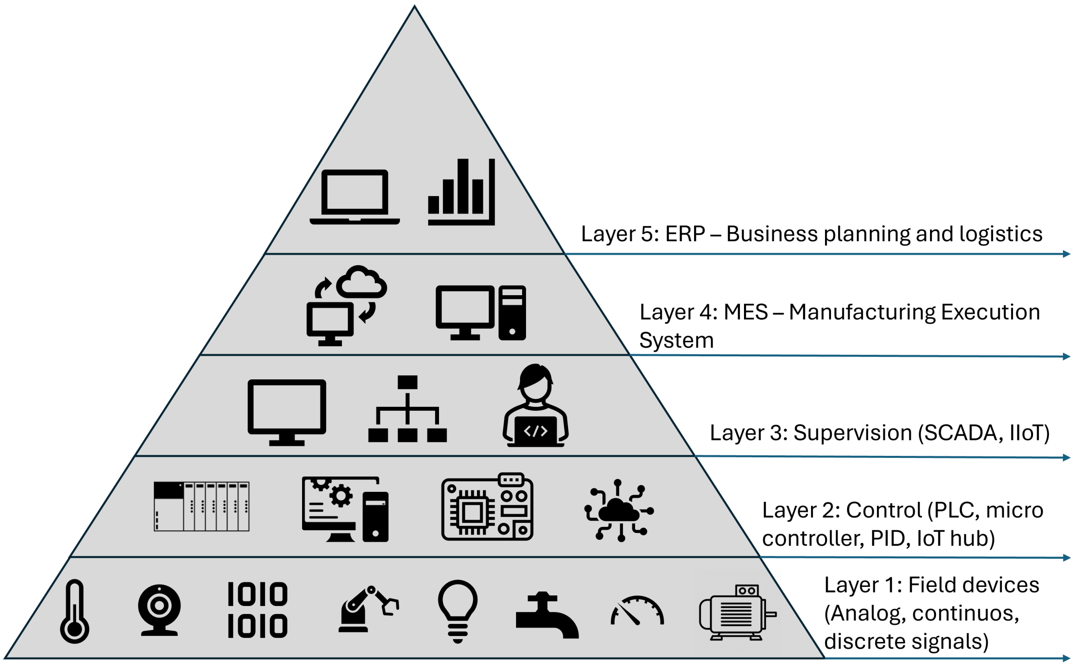

FIGURE 17. The automation pyramid showcasing the scope of the various layers of automation. The number of devices reduces as you go higher up the pyramid, however, the size of data and its complexity increases.

FIGURE 18. Instances of oranges on a roller conveyor.

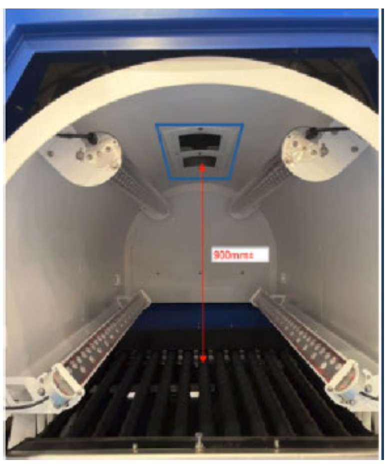

FIGURE 19. Acquisition chamber of Multiscan.

Once the fruits arrive into the acquisition chamber (right behind the grey curtain at the end of the conveyor, depicted on the rightmost of Fig. 18), they are captured by means of Sony IMX429 camera (marked with a blue box in Fig. 19), which is set up in a top-down position at about 90cm from the conveyor plane. The oranges were exposed to cool white LEDs (the four tubes at the angles of Fig. 19) to ensure a uniform lighting source. As aforementioned, the oranges are shot from different viewpoints by the camera, then the multiple view images of each fruit are put together to form a single collage image as shown in Fig. 20, which is used to train the grading deep learning model along with the class label. One the deep learning model was trained, it was deployed to perform the grading task in real time and has shown interesting grading capabilities. In this particular case study, the grading aims at allocating different grades to different customers, which entails different pricing too.

2) CASE STUDY 2

Marumi Foods Co., Ltd. [264] specializes in the processing of radishes, to produce their end product which is frozen and (freshly) grated Daikon radish. Each of the final packages of the frozen and grated radish weigh about 500 grams. Furthermore, they are cold (around -30 ° C to -40 ° C) and slippery, further increasing the handling difficulty and making prolonged working difficult hard for the human workers. In order to reduce the burden on the employees and to offset the increasing labour costs in the future, a full scale automation system for box packaging was installed in 2021.

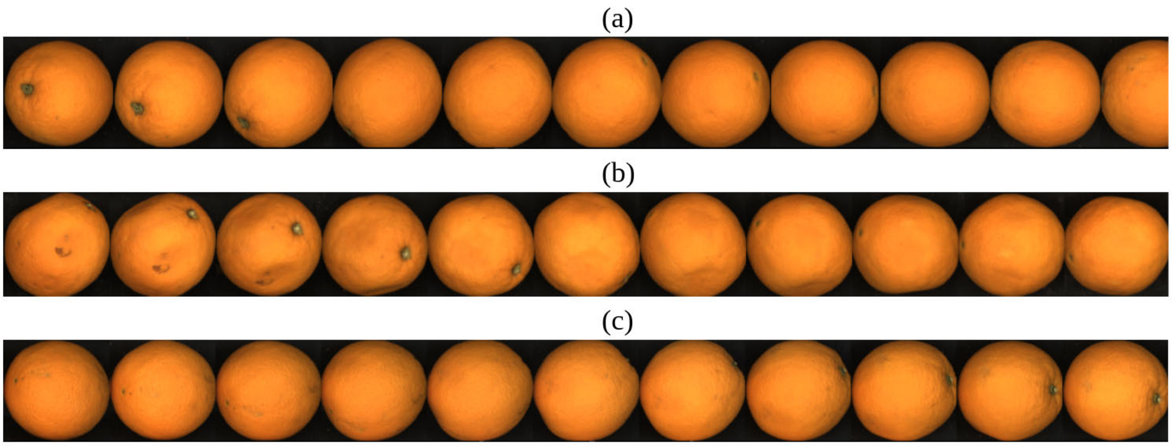

FIGURE 20. Examples from each class. (a) Good, (b) Bad, and (c) Undefined. Each row represents the same orange captured from different angles.

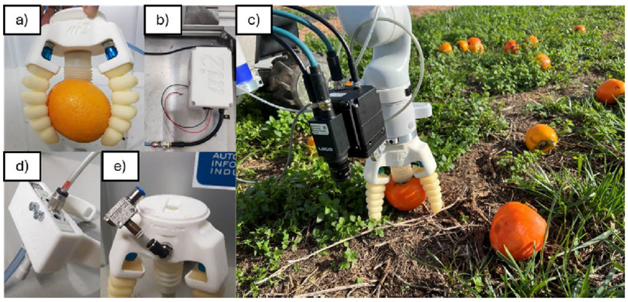

FIGURE 21. Robot gripper used and their main components: a) The soft robotic pneumatic three fingers, b) Developed air compressor for the mobile robot, c) Robot gripper in action picking from the floor an orange, d) Electrovalve 5/2 to control gripper operation, e) air quick exhaust valve.

The implemented solution for the box packaging solution consists of

1) a Kawasaki RS020N [265] vertically articulated robot responsible for the stacking/unstacking of the trays (containers)
2) a suction conveyance device
3) a conveyer system
4) a workpiece alignment and box packing mechanism
5) a case former and
6) a case sealer

The automated system demonstrates a compact and efficient approach to handling frozen food products, fitting within a space of approximately four square meters. The process starts with 30 stacked trays being retrieved from the freezer and unstacked by a robot. The robot transfers each tray onto a conveyor, where the six packs per tray are picked up by a suction conveyor. Simultaneously, the empty trays are moved to the stacking area. The packed products are then transferred to the alignment and box-packing area, where they are assembled into cardboard boxes containing 20 packs each. Finally, the boxes are sealed and directed to the shipping area. This entire process, which involves nine completed boxes per cycle, takes approximately seven to eight minutes per rack.

This system has notably streamlined operations by reducing the number of workers required for box packing from four or five to one or two, and by eliminating direct contact between workers and the frozen products, thus preventing thawing. Key innovations include the robot's proximity sensor, which adjusts unstacking based on tray height, and the use of a drop impact mechanism to facilitate the removal of frozen packs from trays. Additionally, the system features a unique packing mechanism where boxes are initially laid on their sides and filled through a side-sliding method before being uprighted and sealed [266].

3) CASE STUDY 3

AINIA is a research association in the agri-food industry. In the FOODCOLLECT project (IMDEEA/2021/74), AINIA aims to automate the collection of fallen fruit (oranges and persimmons) using a Kinova Gen3 collaborative robot mounted on Robotnik's RB-Summit mobile robot. The product is located using a 3D machine vision camera. At the beginning of the project, the Robotiq 2F 140 under-actuated two-finger electric gripper was used. This gripper allows the fingers to adapt to the shape of the products, increasing the contact points. However, using two fingers limited the product's stability during the handling process and damaged the more mature products.

A new three-finger gripper (Fig. 21) with flexible fingers pneumatically actuated was developed for ai2-UPV (Institute of Automation and Industrial Informatics, Universitat Politècnica de València). The developed gripper can handle nearly spherical products with sizes between 50 and 100 millimeters in diameter and weights between 150 and 300 grams. The fingers are made of TPU material with a shore hardness of 92A and manufactured in 3D printing using selective laser sintering technology. Their maximum operating pressure is 3 bar. The chassis is made of polyamide. In the central part, there is a VF38/5CN multi-bellows suction cup that serves as a stop for the product, stabilizing it. This suction cup can be connected to a vacuum circuit if necessary. The total weight of the gripper is 380 grams 63% less than the old one. The closing and opening time is 0.3 seconds at 3 bar. A quick exhaust valve opens the gripper's fingers more quickly.

One of the main challenges was using compressed air since mobile robots do not have this service; therefore, it was necessary to develop a small compressor that suited the product's needs. For this purpose, the Xiaomi 1S mini compressor was adapted with a specific electronic circuit for analog control of the required pressure. The new models of industrial mini compressors fulfill this function, such as the SMC CRP model. More than 100 persimmons and oranges have been handled without causing any damage to the products. The reduced weight of the gripper has facilitated the robot's operation, with the main drawback being the use of compressed air in mobile robots which requires an extra installation.

V. DISCUSSIONS AND CONCLUSION

This review is a comprehensive exploration of the current state of automation in the primary processing of food, with a special emphasis on the capabilities and utilization of robotic manipulators, end-effectors, machine vision, and material transportation systems. From the fundamental elements of a vision-based sensing system to nuanced applications of various types of transportation systems, this manuscript comprises a wide expanse of information. We would like to highlight some of the key takeaways, for the sensing and actuation systems, which we identified during the compilation of this manuscript

Despite the ongoing evolution in machine vision, certain bottlenecks persist in both the hardware aspect and processing the captured data. Many machine vision solutions are deployed in environmental conditions, which can impede their functioning and degrade the physical quality of sensors over time, owing to factors such as dust, temperature and humidity. Furthermore, most existing systems require initial data to make experimental analysis, parameter tuning, model selection, and model training in the case of supervised machine learning paradigms. Regarding supervised machine learning techniques, two options are envisioned: starting the training from scratch or initiating the training based on a model previously pre-trained on similar data/tasks. The latter option is favoured for more convincing results. However, this is often unattainable due to the lack of such pre-trained models.

In order to overcome the aforementioned machine vision challenges some of the potential solutions include: the installation of separate/isolated vision-based product inspection zones with optimal operating conditions; establishing universal dataset repositories that can be exploited by interested stakeholders and solution developers; and developing universal grading models that could serve as a starting point for solution developers.

Robotic manipulators have been widely gaining traction in many industrial sectors, and are increasingly being utilized in primary food processing at varying levels. Food safe robotic systems coupled with vision systems are currently capable of performing material handling applications in current food processing settings. However, the existing solutions predominantly cater to the pick and place and packaging applications on rigid food stuff, which exhibit minimal unpredictable deformation. Alternately, for operations such as food manipulation the robot-based solutions are currently being explored and researched, and not many commercially available solutions cater to directly handle and process many of the deformable, viscoelastic food types. Improvements in modelling the physical characteristics of food; increasing the accessibility of food-safe force controlled manipulators to incorporate higher degrees of precision while manipulating deformable/delicate foods; incorporating suitable (pre-trained) artificial intelligence models to monitor the behavior of the manipulated product and perform necessary corrective actions in real time, are the next logical steps to create market ready robotic systems for processing food.

Robotic manipulators depend on appropriate end-effectors to efficiently perform their manipulation/value-addition operations. End-effectors come in various shapes, sizes, and mechanisms for operations, with varying levels of control and operation time. The operational requirements of the end-effectors are mainly dependant on the process parameters to be satisfied. There is an extensive range of end-effectors available in the market and newer variations are constantly being developed to handle the ever-evolving requirements of the industry.

Transportation systems are an integral part of many industrial sectors, and the systems with hygienic and sanitation features naturally find their way into the food sector. From the ability of these systems to convey a wide range of food types, ranging from powder/particulate to large deformable portions of meat, showcases the versatility of the market ready systems. The future developments regarding the conveying systems, is to efficiently incorporate value addition processes, and decrease the lead time required for the production operation.

In conclusion, this review has highlighted the critical role of automation technologies modernizing primary food processing, and bridged gaps in the existing literature in this niche domain. These integrated solutions are pivotal for enhancing efficiency, safety, and quality, meeting the increasing demands of global food production. As the population grows and the industry evolves, the synergy among these technologies will continue to be the cornerstone of innovation and sustainability in food processing

REFERENCES

[1] United Nations. *Population | United Nations*. Accessed: Mar. 25, 2024. [Online]. Available: https://www.un.org/en/global-issues/population

[2] V. Gaigbe-Togbe, L. Zeifman, T. Spoorenberg, D. Gu, and L. Bassarsky. (Jul. 2022). *World Population Prospects 2022: Summary of Results*. [Online]. Available: https://www.un.org/development/desa/pd/content/World-Population-Prospects-2022

[3] (2024). *Global Manufacturing: Food—Industry Insights & Data Analysis | Statista*. Accessed: Feb. 23, 2024. [Online]. Available: https://www.statista.com/study/57188/manufacturing-food—global

[4] *Data & Trends of the European Food and Drink Industry 2023—FoodDrinkEurope*. Accessed: Feb. 22, 2024. [Online]. Available: https://www.fooddrinkeurope.eu/resource/data-trends-of-the-european-food-and-drink-industry-2023
[5] *Eurostat Statistics Explained: Businesses in the Accommodation and Food Services Sector*. Accessed: Feb. 23, 2024. [Online]. Available: https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Businesses_in_the_accommodation_and_food_services_sector
[6] *Eurostat Statistics Explained: Wages and Labour Costs*. Accessed: Feb. 23, 2024. [Online]. Available: https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Wages_and_labour_costs
[7] J. Hawksworth, R. Berriman, and S. Goel. (Feb. 2018). *Will Robots Really Steal Our Jobs?*. Accessed: Feb. 23, 2024. [Online]. Available: https://www.pwc.com/hu/hu/kiadvanyok/assets/pdf/impact_of_automation_on_jobs.pdf
[8] A. D. Tripathi, R. Mishra, K. K. Maurya, R. B. Singh, and D. W. Wilson, "Estimates for world population and global food availability for global health," in *The Role of Functional Food Security in Global Health*, R. B. Singh, R. R. Watson, and T. Takahashi, Eds., New York, NY, USA: Academic, 2019, pp. 3–24. [Online]. Available: https://www.sciencedirect.com/science/article/pii/B9780128131480000013
[9] G. Chandrasiri, K. Wijenayake, and U. Arachchige, "Development of automated systems for the implementation of food processing," *J. Res. Technol. Eng.*, vol. 1, no. 3, p. 18, 2022.
[10] A. Baregheh, J. Rowley, S. Sambrook, and D. Davies, "Innovation in food sector SMEs," *J. Small Bus. Enterprise Develop.*, vol. 19, no. 2, pp. 300–321, May 2012.
[11] *SMEs—FoodDrinkEurope*. Accessed: Feb. 28, 2024. [Online]. Available: https://www.fooddrinkeurope.eu/policy-area/smes
[12] "Lean and agile in small- and medium-sized enterprises: Complementary or incompatible?" *South Afr. J. Bus. Manage.*, vol. 49, no. 1, pp. 1–9, May 2018. [Online]. Available: https://sajbm.org/index.php/sajbm/article/view/11/205
[13] G. A. Nayik, "Robotics and food technology: A mini review," *J. Nutrition Food Sci.*, vol. 5, no. 4, pp. 1–11, 2015.
[14] M. A. Augustin, M. Riley, R. Stockmann, L. Bennett, A. Kahl, T. Lockett, M. Osmond, P. Sanguansri, W. Stonehouse, I. Zajac, and L. Cobiac, "Role of food processing in food and nutrition security," *Trends Food Sci. Technol.*, vol. 56, pp. 115–125, Oct. 2016.
[15] *FAO—Processed Foods for Improved Livelihoods*. Accessed: Feb. 12, 2024. [Online]. Available: https://www.fao.org/3/y5113e/y5113e03.htm
[16] R. Prakash and M. R. Ravindra, "Robotic engineering: A tool for quality and safety of foods," in *Handbook of Research on Food Processing and Preservation Technologies: Volume 5: Emerging Techniques for Food Processing, Quality, and Safety Assurance*. Palm Bay, FL, USA: Apple Academic Press, 2021, p. 311.
[17] M. Weston, S. Geng, and R. Chandrawati, "Food sensors: Challenges and opportunities," *Adv. Mater. Technol.*, vol. 6, no. 5, May 2021, Art. no. 2001242.
[18] Z. H. Khan, A. Khalid, and J. Iqbal, "Towards realizing robotic potential in future intelligent food manufacturing systems," *Innov. Food Sci. Emerg. Technol.*, vol. 48, pp. 11–24, Aug. 2018.
[19] IFR International Federation of Robotics. *International Federation of Robotics, WR Industrial Robots 2023*. Accessed: Feb. 13, 2024. [Online]. Available: https://ifr.org/img/worldrobotics/Executive_Summary_WR_Industrial_Robots_2023.pdf
[20] F. Bader and S. Rahimifard, "Challenges for industrial robot applications in food manufacturing," in *Proc. 2nd Int. Symp. Comput. Sci. Intell. Control*, Sep. 2018, pp. 1–8.
[21] A. Taheri-Garavand, S. Fatahi, M. Omid, and Y. Makino, "Meat quality evaluation based on computer vision technique: A review," *Meat Sci.*, vol. 156, pp. 183–195, Oct. 2019.
[22] N. S. N. A. Aziz, S. M. Daud, R. A. Dziyauddin, M. Z. Adam, and A. Azizan, "A review on computer vision technology for monitoring poultry farm—Application, hardware, and software," *IEEE Access*, vol. 9, pp. 12431–12445, 2021.
[23] L. Franceschelli, A. Berardinelli, S. Dabbou, L. Ragni, and M. Tartagni, "Sensing technology for fish freshness and safety: A review," *Sensors*, vol. 21, no. 4, p. 1373, Feb. 2021.
[24] A. Bhargava and A. Bansal, "Fruits and vegetables quality evaluation using computer vision: A review," *J. King Saud Univ. Comput. Inf. Sci.*, vol. 33, no. 3, pp. 243–257, Mar. 2021.
[25] L. Zhu, P. Spachos, E. Pensini, and K. N. Plataniotis, "Deep learning and machine vision for food processing: A survey," *Current Res. Food Sci.*, vol. 4, pp. 233–249, Sep. 2021.
[26] *Scopus—Document Search*. Accessed: Aug. 20, 2024. [Online]. Available: https://www.scopus.com/search/form.uri?display=basic&zone=header&origin=#basic
[27] *VOSviewer—Visualizing Scientific Landscapes*. Accessed: Aug. 20, 2024. [Online]. Available: https://www.vosviewer.com
[28] P. Kumar, D. Singh, and J. Bhamu, "Machine vision in industry 4.0: Applications, challenges and future directions," in *Machine Vision for Industry 4.0*. Boca Raton, FL, USA: CRC Press, 2022, pp. 263–284.
[29] S. Sabzi, Y. Abbaspour-Gilandeh, and H. Javadikia, "Machine vision system for the automatic segmentation of plants under different lighting conditions," *Biosystems Eng.*, vol. 161, pp. 157–173, Sep. 2017.
[30] F. Collier, "Machine vision lighting," *Quality*, vol. 61, no. 12, p. 31, 2022.
[31] S. Kinney, "Three challenges in machine vision lighting today and how to solve them," *Quality*, vol. 61, no. 5, p. 30, 2022.
[32] E. McMenamin, "Lighting," *Quality*, pp. 14–15, Mar. 2018. [Online]. Available: https://www.proquest.com/docview/2049661095?pq-origsite=gscholar&fromopenview=true&sourcetype=Scholarly%20Journals
[33] C. Steger, M. Ulrich, and C. Wiedemann, *Machine Vision Algorithms and Applications*. Hoboken, NJ, USA: Wiley, 2018.
[34] D. Martin, "A practical guide to machine vision lighting," in *Proc. Midwest Sales Support Manager, Adv Illum*, 2007, pp. 1–3.
[35] O. E. Apolo-Apolo, J. Martínez-Guanter, G. Egea, P. Raja, and M. Pérez-Ruiz, "Deep learning techniques for estimation of the yield and size of citrus fruits using a UAV," *Eur. J. Agronomy*, vol. 115, Apr. 2020, Art. no. 126030.
[36] O. Aiadi, B. Khaldi, M. L. Kherfi, M. L. Mekhalfi, and A. Alharbi, "Date fruit sorting based on deep learning and discriminant correlation analysis," *IEEE Access*, vol. 10, pp. 79655–79668, 2022.
[37] M. Kerkech, A. Hafiane, and R. Canals, "Vine disease detection in UAV multispectral images using optimized image registration and deep learning segmentation approach," *Comput. Electron. Agricult.*, vol. 174, Jul. 2020, Art. no. 105446.
[38] C. A. Garillos-Manliguez and J. Y. Chiang, "Multimodal deep learning and visible-light and hyperspectral imaging for fruit maturity estimation," *Sensors*, vol. 21, no. 4, p. 1288, Feb. 2021.
[39] A. McGlone, "Scanning technologies for horticultural packhouses," AUSVEG, Victoria, BC, Canada, Tech. Rep. ST19022, 2021.
[40] B. Milovanovic, V. Tomovic, I. Djekic, J. Miocinovic, B. G. Solowiej, J. M. Lorenzo, F. J. Barba, and I. Tomasevic, "Colour assessment of milk and milk products using computer vision system and colorimeter," *Int. Dairy J.*, vol. 120, Sep. 2021, Art. no. 105084.
[41] D. Choi, W. S. Lee, R. Ehsani, and F. M. Roka, "A machine vision system for quantification of citrus fruit dropped on the ground under the canopy," *Trans. ASABE*, vol. 58, no. 4, pp. 933–946, 2015.
[42] Ø. Sture, E. R. Øye, A. Skavhaug, and J. R. Mathiassen, "A 3D machine vision system for quality grading of Atlantic salmon," *Comput. Electron. Agricult.*, vol. 123, pp. 142–148, Apr. 2016.
[43] H. A. M. Williams, M. H. Jones, M. Nejati, M. J. Seabright, J. Bell, N. D. Penhall, J. J. Barnett, M. D. Duke, A. J. Scarfe, H. S. Ahn, J. Lim, and B. A. MacDonald, "Robotic kiwifruit harvesting using machine vision, convolutional neural networks, and robotic arms," *Biosystems Eng.*, vol. 181, pp. 140–156, May 2019.
[44] T. Yoshida, T. Kawahara, and T. Fukao, "Fruit recognition method for a harvesting robot with RGB-D cameras," *ROBOMECH J.*, vol. 9, no. 1, p. 15, Dec. 2022.
[45] J. Feng, L. Zeng, and L. He, "Apple fruit recognition algorithm based on multi-spectral dynamic image analysis," *Sensors*, vol. 19, no. 4, p. 949, Feb. 2019.
[46] E. Guzmán, V. Baeten, J. A. F. Pierna, and J. A. García-Mesa, "Infrared machine vision system for the automatic detection of olive fruit quality," *Talanta*, vol. 116, pp. 894–898, Nov. 2013.
[47] K. N. E. Alam Siddiquee, M. S. Islam, M. Y. U. Dowla, K. M. Rezaul, and V. Grout, "Detection, quantification and classification of ripened tomatoes: A comparative analysis of image processing and machine learning," *IET Image Process.*, vol. 14, no. 11, pp. 2442–2456, Sep. 2020.
[48] F. Gao, W. Fang, X. Sun, Z. Wu, G. Zhao, G. Li, R. Li, L. Fu, and Q. Zhang, "A novel apple fruit detection and counting methodology based on deep learning and trunk tracking in modern orchard," *Comput. Electron. Agricult.*, vol. 197, Jun. 2022, Art. no. 107000.

[49] I. Sa, J. Y. Lim, H. S. Ahn, and B. MacDonald, "DeepNIR: Datasets for generating synthetic NIR images and improved fruit detection system using deep learning techniques," *Sensors*, vol. 22, no. 13, p. 4721, Jun. 2022.
[50] L. Liu, Z. Li, Y. Lan, Y. Shi, and Y. Cui, "Design of a tomato classifier based on machine vision," *PLoS ONE*, vol. 14, no. 7, Jul. 2019, Art. no. e0219803.
[51] H. Altaheri, M. Alsulaiman, and G. Muhammad, "Date fruit classification for robotic harvesting in a natural environment using deep learning," *IEEE Access*, vol. 7, pp. 117115–117133, 2019.
[52] Y. Xiong, Y. Li, C. Wang, H. Shi, S. Wang, C. Yong, Y. Gong, W. Zhang, and X. Zou, "Non-destructive detection of chicken freshness based on electronic nose technology and transfer learning," *Agriculture*, vol. 13, no. 2, p. 496, Feb. 2023.
[53] T. Dewi, P. Risma, and Y. Oktarina, "Fruit sorting robot based on color and size for an agricultural product packaging system," *Bull. Electr. Eng. Informat.*, vol. 9, no. 4, pp. 1438–1445, Aug. 2020.
[54] C. Zhang, D. Zhang, Y. Su, X. Zheng, S. Li, and L. Chen, "Research on the authenticity of mutton based on machine vision technology," *Foods*, vol. 11, no. 22, p. 3732, Nov. 2022.
[55] A. Chauhan and M. Singh, "Computer vision and machine learning based grape fruit cluster detection and yield estimation robot," *J. Sci. Ind. Res.*, vol. 81, pp. 1–7, Aug. 2022.
[56] K. Zhou, Z. Meng, M. He, J. Hou, and T. Li, "Design and test of a sorting device based on machine vision," *IEEE Access*, vol. 8, pp. 27178–27187, 2020.
[57] H. Azarmdel, S. S. Mohtasebi, A. Jafary, H. Behfar, and A. R. Muñoz, "Design and simulation of a vision-based automatic trout fish-processing robot," *Appl. Sci.*, vol. 11, no. 12, p. 5602, Jun. 2021.
[58] L. M. A. Bengua, V. J. D. De Guzman, D. M. S. Macunat, E. D. Villaverde, A. T. Mahusay, R. R. Maaliw, A. C. Lagman, and A. S. Alon, "Salted EGG cleaning and grading system using machine vision," in *Proc. IEEE World AI IoT Congr. (AIIoT)*, 2022, pp. 489–493.
[59] L. Hou, Z. Liu, J. You, Y. Liu, J. Xiang, J. Zhou, and Y. Pan, "Tomato sorting system based on machine vision," *Electronics*, vol. 13, no. 11, p. 2114, May 2024.
[60] G. Vilcamiza, N. Trelles, L. Vinces, and J. Oliden, "A coffee bean classifier system by roast quality using convolutional neural networks and computer vision implemented in an Nvidia Jetson Nano," in *Proc. Congreso Internacional de Innovación y Tendencias en Ingenierìa (CONIITI)*, 2022, pp. 1–6.
[61] A. Kuswantori, T. Suesut, W. Tangsrirat, G. Schleining, and N. Nunak, "Fish detection and classification for automatic sorting system with an optimized Yolo algorithm," *Appl. Sci.*, vol. 13, no. 6, p. 3812, Mar. 2023.
[62] P. Cisar, D. Bekkozhayeva, O. Movchan, M. Saberioon, and R. Schraml, "Computer vision based individual fish identification using skin dot pattern," *Sci. Rep.*, vol. 11, no. 1, p. 16904, Aug. 2021.
[63] E. Olaniyi, Y. Lu, A. T. Sukumaran, T. Jarvis, and C. Rowe, "Non-destructive assessment of white striping in broiler breast meat using structured-illumination reflectance imaging with deep learning," *J. ASABE*, vol. 66, no. 6, pp. 1437–1447, 2023.
[64] K.-D. Kwon, A. Lee, J. Lim, S. Cho, W. Lee, B.-K. Cho, and Y. Seo, "Quality grading of hanwoo (Korean native cattle breed) sub-images using convolutional neural network," *Korean J. Agricult. Sci.*, vol. 47, no. 4, pp. 1109–1122, Dec. 2020.
[65] M. Lecca, A. Torresani, and F. Remondino, "Comprehensive evaluation of image enhancement for unsupervised image description and matching," *IET Image Process.*, vol. 14, no. 16, pp. 4329–4339, Dec. 2020. [Online]. Available: https://digital-library.theiet.org/content/journals/10.1049/iet-ipr.2020.1129
[66] Y. Wang, Q. Huang, and J. Hu, "Adaptive enhancement for non-uniform illumination images via pixel-wise histogram modification and color reconstruction," in *Proc. IEEE 3rd Int. Conf. Signal Image Process. (ICSIP)*, 2018, pp. 220–224.
[67] Y. Ueda, D. Moriyama, T. Koga, and N. Suetake, "Histogram specification-based image enhancement for backlit image," in *Proc. IEEE Int. Conf. Image Process. (ICIP)*, Oct. 2020, pp. 958–962.
[68] N. Banic and S. Loncaric, "Firefly: A hardware-friendly real-time local brightness adjustment method," in *Proc. IEEE Int. Conf. Image Process. (ICIP)*, Sep. 2015, pp. 3951–3955.
[69] M. Lecca, "STAR: A segmentation-based approximation of point-based sampling Milan retinex for color image enhancement," *IEEE Trans. Image Process.*, vol. 27, no. 12, pp. 5802–5812, Dec. 2018.
[70] M. Lecca and S. Messelodi, "SuPeR: Milan retinex implementation exploiting a regular image grid," *J. Opt. Soc. Amer. A, Opt. Image Sci.*, vol. 36, no. 8, p. 1423, Aug. 2019. [Online]. Available: http://josaa.osa.org/abstract.cfm?URI=josaa-36-8-1423
[71] M. Lecca, "A Retinex inspired bilateral filter for enhancing images under difficult light conditions," in *Proc. VISIGRAPP (4: VISAPP)*, 2021, pp. 76–86.
[72] D. Agrawal, A. C. Yadav, and P. K. Tyagi, "Low-light and hazy image enhancement using retinex theory and wavelet transform fusion," *Multimedia Tools Appl.*, vol. 83, no. 29, pp. 72519–72536, Feb. 2024.
[73] W. Wu, J. Weng, P. Zhang, X. Wang, W. Yang, and J. Jiang, "URetinex-net: Retinex-based deep unfolding network for low-light image enhancement," in *Proc. IEEE/CVF Conf. Comput. Vis. Pattern Recognit.*, Sep. 2022, pp. 5901–5910.
[74] X. Li, W. Wang, X. Feng, and M. Li, "Deep parametric retinex decomposition model for low-light image enhancement," *Comput. Vis. Image Understand.*, vol. 241, Apr. 2024, Art. no. 103948. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S1077314224000298
[75] D. Xie, H. Xing, L. Chen, and S. Hao, "A lightness-aware loss for low-light image enhancement," *Pattern Recognit. Lett.*, vol. 179, pp. 123–129, Mar. 2024. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0167865524000448
[76] H. Pan, B. Gao, X. Wang, C. Jiang, and P. Chen, "DICNet: Achieve low-light image enhancement with image decomposition, illumination enhancement, and color restoration," *Vis. Comput.*, vol. 40, no. 10, pp. 6779–6795, Oct. 2024.
[77] X. Fu, D. Zeng, Y. Huang, Y. Liao, X. Ding, and J. Paisley, "A fusion-based enhancing method for weakly illuminated images," *Signal Process.*, vol. 129, pp. 82–96, Dec. 2016.
[78] Q. Wang, X. Fu, X.-P. Zhang, and X. Ding, "A fusion-based method for single backlit image enhancement," in *Proc. IEEE Int. Conf. Image Process. (ICIP)*, Phoenix, AZ, USA, Sep. 2016, pp. 4077–4081.
[79] M. Lecca, "Backlight and spotlight image enhancement based on von kries model," *Social Netw. Comput. Sci.*, vol. 4, no. 5, p. 680, Sep. 2023.
[80] F. Lv, F. Lu, J. Wu, and C. Lim, "MBLLEN: Low-light image/video enhancement using CNNs," in *Proc. BMVC*, Newcastel, U.K., 2018, p. 220.
[81] L. Zhang, L. Zhang, X. Liu, Y. Shen, S. Zhang, and S. Zhao, "Zero-shot restoration of back-lit images using deep internal learning," in *Proc. 27th ACM Int. Conf. Multimedia*, Oct. 2019, pp. 1623–1631.
[82] Y. Jiang, X. Gong, D. Liu, Y. Cheng, C. Fang, X. Shen, J. Yang, P. Zhou, and Z. Wang, "EnlightenGAN: Deep light enhancement without paired supervision," *IEEE Trans. Image Process.*, vol. 30, pp. 2340–2349, 2021.
[83] M. Ebner, "Color constancy," in *Computer Vision: A Reference Guide*. Cham, Switzerland: Springer, 2021, pp. 168–175.
[84] M. Lecca, "On the von Kries model: Estimation, dependence on light and device, and applications," in *Advances in Low-Level Color Image Processing*. Dordrecht, The Netherlands: Springer, 2014, pp. 95–135.
[85] M. Bertalmío, *Vision Models for High Dynamic Range and Wide Colour Gamut Imaging*. Cambridge, MA, USA: Academic, 2020.
[86] H. Le, T. Jeong, A. Abdelhamed, H. J. Shin, and M. S. Brown, "GamutNet: Restoring wide-gamut colors for camera-captured images," *Color Imag. Conf.*, vol. 29, no. 1, pp. 7–12, Nov. 2021.
[87] A. Dingli, F. Haddod, and C. Klüver, *Artificial Intelligence in Industry 4.0*, vol. 928. Cham, Switzerland: Springer, 2021.
[88] J. Zhang and D. Tao, "Empowering things with intelligence: A survey of the progress, challenges, and opportunities in artificial intelligence of things," *IEEE Internet Things J.*, vol. 8, no. 10, pp. 7789–7817, May 2021.
[89] C. Zhang and Y. Lu, "Study on artificial intelligence: The state of the art and future prospects," *J. Ind. Inf. Integr.*, vol. 23, Sep. 2021, Art. no. 100224.
[90] M. Alam, M. D. Samad, L. Vidyaratne, A. Glandon, and K. M. Iftekharuddin, "Survey on deep neural networks in speech and vision systems," *Neurocomputing*, vol. 417, pp. 302–321, Dec. 2020.
[91] J. Waring, C. Lindvall, and R. Umeton, "Automated machine learning: Review of the state-of-the-art and opportunities for healthcare," *Artif. Intell. Med.*, vol. 104, Apr. 2020, Art. no. 101822.
[92] M. F. Dixon, I. Halperin, and P. Bilokon, *Machine Learning in Finance*, vol. 1170. Cham, Switzerland: Springer, 2020.
[93] A. Dogan and D. Birant, "Machine learning and data mining in manufacturing," *Expert Syst. Appl.*, vol. 166, Mar. 2021, Art. no. 114060.

[94] M. Woschank, E. Rauch, and H. Zsifkovits, "A review of further directions for artificial intelligence, machine learning, and deep learning in smart logistics," *Sustainability*, vol. 12, no. 9, p. 3760, May 2020.
[95] D. I. R. Rai, M. K. Tiwari, and A. Dolgui, "Machine learning in manufacturing and industry 4.0 applications," *Int. J. Prod. Res.*, vol. 59, no. 16, pp. 4773–4778, 2021.
[96] D. Rolnick, P. L. Donti, L. H. Kaack, K. Kochanski, A. Lacoste, K. Sankaran, A. S. Ross, N. Milojevic-Dupont, N. Jaques, and A. Waldman-Brown, "Tackling climate change with machine learning," *ACM Comput. Surv.*, vol. 55, no. 2, pp. 1–96, Feb. 2022.
[97] K. He, X. Zhang, S. Ren, and J. Sun, "Deep residual learning for image recognition," in *Proc. CVPR*, vol. 16, Jul. 2016, pp. 770–778.
[98] Y. Gulzar, "Fruit image classification model based on MobileNetV2 with deep transfer learning technique," *Sustainability*, vol. 15, no. 3, p. 1906, Jan. 2023.
[99] Z. Zhu, K. Lin, A. K. Jain, and J. Zhou, "Transfer learning in deep reinforcement learning: A survey," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 45, no. 11, pp. 1–20, Nov. 2023.
[100] Z. Li, C. Peng, G. Yu, X. Zhang, Y. Deng, and J. Sun, "DetNet: Design backbone for object detection," in *Proc. Eur. Conf. Comput. Vis. (ECCV)*, 2018, pp. 334–350.
[101] S. Dong, P. Wang, and K. Abbas, "A survey on deep learning and its applications," *Comput. Sci. Rev.*, vol. 40, May 2021, Art. no. 100379.
[102] Z. Zou, K. Chen, Z. Shi, Y. Guo, and J. Ye, "Object detection in 20 years: A survey," *Proc. IEEE*, vol. 111, no. 3, pp. 257–276, Mar. 2023.
[103] R. Tang, Y. Lei, B. Luo, J. Zhang, and J. Mu, "YOLOv7-plum: Advancing plum fruit detection in natural environments with deep learning," *Plants*, vol. 12, no. 15, p. 2883, Aug. 2023.
[104] G. A. Leiva-Valenzuela and J. M. Aguilera, "Automatic detection of orientation and diseases in blueberries using image analysis to improve their postharvest storage quality," *Food Control*, vol. 33, no. 1, pp. 166–173, Sep. 2013.
[105] M. S. Mahmud, Q. U. Zaman, T. J. Esau, Y. K. Chang, G. W. Price, and B. Prithiviraj, "Real-time detection of strawberry powdery mildew disease using a mobile machine vision system," *Agronomy*, vol. 10, no. 7, p. 1027, Jul. 2020.
[106] P. Wan, A. Toudeshki, H. Tan, and R. Ehsani, "A methodology for fresh tomato maturity detection using computer vision," *Comput. Electron. Agricult.*, vol. 146, pp. 43–50, Mar. 2018.
[107] M. De Silva and D. Brown, "Multispectral plant disease detection with vision transformer–convolutional neural network hybrid approaches," *Sensors*, vol. 23, no. 20, p. 8531, Oct. 2023.
[108] Y. Yang, Z. Liu, M. Huang, Q. Zhu, and X. Zhao, "Automatic detection of multi-type defects on potatoes using multispectral imaging combined with a deep learning model," *J. Food Eng.*, vol. 336, Jan. 2023, Art. no. 111213.
[109] D. Unay, "Deep learning based automatic grading of bi-colored apples using multispectral images," *Multimedia Tools Appl.*, vol. 81, no. 27, pp. 38237–38252, Nov. 2022.
[110] W. Wang and C. Li, "A multimodal machine vision system for quality inspection of onions," *J. Food Eng.*, vol. 166, pp. 291–301, Dec. 2015.
[111] A. R. Mesa and J. Y. Chiang, "Multi-input deep learning model with RGB and hyperspectral imaging for banana grading," *Agriculture*, vol. 11, no. 8, p. 687, Jul. 2021.
[112] M. L. Mekhalfi, C. Nicolò, I. Ianniello, F. Calamita, R. Goller, M. Barazzuol, and F. Melgani, "Vision system for automatic on-tree kiwifruit counting and yield estimation," *Sensors*, vol. 20, no. 15, p. 4214, Jul. 2020.
[113] A. Gongal, A. Silwal, S. Amatya, M. Karkee, Q. Zhang, and K. Lewis, "Apple crop-load estimation with over-the-row machine vision system," *Comput. Electron. Agricult.*, vol. 120, pp. 26–35, Jan. 2016.
[114] Z. Wang, J. Underwood, and K. B. Walsh, "Machine vision assessment of mango orchard flowering," *Comput. Electron. Agricult.*, vol. 151, pp. 501–511, Aug. 2018.
[115] H. Azarmdel, S. S. Mohtasebi, A. Jafari, and A. R. Muñoz, "Developing an orientation and cutting point determination algorithm for a trout fish processing system using machine vision," *Comput. Electron. Agricult.*, vol. 162, pp. 613–629, Jul. 2019.
[116] G. G. Monkman, K. Hyder, M. J. Kaiser, and F. P. Vidal, "Using machine vision to estimate fish length from images using regional convolutional neural networks," *Methods Ecology Evol.*, vol. 10, no. 12, pp. 2045–2056, Dec. 2019.
[117] I. Sharmin, N. F. Islam, I. Jahan, T. Ahmed Joye, M. R. Rahman, and M. T. Habib, "Machine vision based local fish recognition," *Social Netw. Appl. Sci.*, vol. 1, no. 12, pp. 1–12, Dec. 2019.
[118] E. Guttormsen, B. Toldnes, M. Bondø, A. Eilertsen, J. T. Gravdahl, and J. R. Mathiassen, "A machine vision system for robust sorting of herring fractions," *Food Bioprocess Technol.*, vol. 9, no. 11, pp. 1893–1900, Nov. 2016.
[119] N. Sengar, M. K. Dutta, and B. Sarkar, "Computer vision based technique for identification of fish quality after pesticide exposure," *Int. J. Food Properties*, vol. 20, pp. 1–15, Dec. 2017.
[120] A. Banwari, R. C. Joshi, N. Sengar, and M. K. Dutta, "Computer vision technique for freshness estimation from segmented eye of fish image," *Ecological Informat.*, vol. 69, Jul. 2022, Art. no. 101602.
[121] J.-L. Xu and D.-W. Sun, "Computer vision detection of salmon muscle gaping using convolutional neural network features," *Food Anal. Methods*, vol. 11, no. 1, pp. 34–47, Jan. 2018.
[122] J.-L. Xu, C. Riccioli, and D.-W. Sun, "Comparison of hyperspectral imaging and computer vision for automatic differentiation of organically and conventionally farmed salmon," *J. Food Eng.*, vol. 196, pp. 170–182, Mar. 2017.
[123] J.-L. Xu and D.-W. Sun, "Identification of freezer burn on frozen salmon surface using hyperspectral imaging and computer vision combined with machine learning algorithm," *Int. J. Refrigeration*, vol. 74, pp. 151–164, Feb. 2017.
[124] N. Teimouri, M. Omid, K. Mollazade, H. Mousazadeh, R. Alimardani, and H. Karstoft, "On-line separation and sorting of chicken portions using a robust vision-based intelligent modelling approach," *Biosystems Eng.*, vol. 167, pp. 8–20, Mar. 2018.
[125] S.-C. Yoon, B. C. Bowker, H. Zhuang, and K. C. Lawrence, "Development of imaging system for online detection of chicken meat with wooden breast condition," *Sensors*, vol. 22, no. 3, p. 1036, Jan. 2022.
[126] I. Nyalala, C. Okinda, N. Makange, T. Korohou, Q. Chao, L. Nyalala, Z. Jiayu, Z. Yi, K. Yousaf, L. Chao, and C. Kunjie, "On-line weight estimation of broiler carcass and cuts by a computer vision system," *Poultry Sci.*, vol. 100, no. 12, Dec. 2021, Art. no. 101474.
[127] S.-Y. Chen, S.-H. Hsu, C.-Y. Ko, and K.-H. Hsu, "Real-time defect and freshness inspection on chicken eggs using hyperspectral imaging," *Food Control*, vol. 150, Aug. 2023, Art. no. 109716.
[128] A. V. Vasileva, E. V. Gorbunova, A. S. Vasilev, V. S. Peretyagin, A. N. Chertov, and V. V. Korotaev, "Assessing exterior egg quality indicators using machine vision," *Brit. Poultry Sci.*, vol. 59, no. 6, pp. 636–645, Nov. 2018.
[129] A. Arsalane, N. El Barbri, A. Tabyaoui, A. Klilou, and K. Rhofir, "The assessment of fresh and spoiled beef meat using a prototype device based on GigE vision camera and DSP," *J. Food Meas. Characterization*, vol. 13, no. 3, pp. 1730–1738, Sep. 2019.
[130] A. Li, C. Li, M. Gao, S. Yang, R. Liu, W. Chen, and K. Xu, "Beef cut classification using multispectral imaging and machine learning method," *Frontiers Nutrition*, vol. 8, Oct. 2021, Art. no. 755007.
[131] E. C. Medeiros, L. M. Almeida, and J. G. D. A. T. Filho, "Computer vision and machine learning for tuna and salmon meat classification," *Informatics*, vol. 8, no. 4, p. 70, Oct. 2021.
[132] M. S. Bondø, J. R. Mathiassen, P. A. Vebenstad, E. Misimi, E. M. Skjøndal Bar, B. Toldnes, and S. Ove Østvik, "An automated salmonid slaughter line using machine vision," *Ind. Robot, Int. J.*, vol. 38, no. 4, pp. 399–405, Jun. 2011.
[133] Z. Xiong, D.-W. Sun, Q. Dai, Z. Han, X.-A. Zeng, and L. Wang, "Application of visible hyperspectral imaging for prediction of springiness of fresh chicken meat," *Food Anal. Methods*, vol. 8, no. 2, pp. 380–391, Feb. 2015.
[134] S. M. Stewart, T. Lauridsen, H. Toft, D. W. Pethick, G. E. Gardner, P. McGilchrist, and M. Christensen, "Objective grading of eye muscle area, intramuscular fat and marbling in Australian beef and Lamb," *Meat Sci.*, vol. 181, Nov. 2021, Art. no. 108358.
[135] *Regulation (Ec), no. 852/2004 of the European Parliament and of the Council of 29 April 2004 on the Hygiene of Foodstuffs*. Accessed: Feb. 13, 2024. [Online]. Available: https://eur-lex.europa.eu/legal-content/EN/TXT/HTML/?uri=CELEX
[136] D. Gabrić, K. Galić, and H. Timmerman, "Cleaning of surfaces," in *Handbook of Hygiene Control in the Food Industry*, 2nd ed., Buckingham, U.K.: Woodhead, Jan. 2016, pp. 447–463.
[137] P. J. Fellows, "Chapter 1—Properties of foods and principles of processing," in *Food Processing Technology*, 5th ed., England, U.K.: Woodhead, Jan. 2022, pp. 3–95.

[138] N. Kondo, "Robotics and automation in the fresh produce industry," in *Robotics and Automation in the Food Industry*. Amsterdam, The Netherlands: Elsevier, 2013, pp. 385–400.
[139] D. P. Smith, "Poultry processing and products," in *Food Processing: Principles and Applications*. Boca Raton, FL, USA: CRC Press, 2014, pp. 549–566.
[140] G. McMurray, "Robotics and automation in the poultry industry: Current technology and future trends," in *Robotics and Automation in the Food Industry*. Buckingham, U.K.: Woodhead, Jan. 2013, pp. 329–353.
[141] W. Xu, Y. He, J. Li, J. Zhou, E. Xu, W. Wang, and D. Liu, "Robotization and intelligent digital systems in the meat cutting industry: From the perspectives of robotic cutting, perception, and digital development," *Trends Food Sci. Technol.*, vol. 135, pp. 234–251, May 2023.
[142] B. A. Aly, T. Low, D. Long, C. Baillie, and P. Brett, "Robotics and sensing technologies in red meat processing: A review," *Trends Food Sci. Technol.*, vol. 137, pp. 142–155, Jul. 2023.
[143] J. Kim, Y.-K. Kwon, H.-W. Kim, K.-H. Seol, and B.-K. Cho, "Robot technology for pork and beef meat slaughtering process: A review," *Animals*, vol. 13, no. 4, p. 651, Feb. 2023.
[144] S. Suri, A. Jain, N. Verma, and N. Prasertpoj, "SCARA industrial automation robot," in *Proc. Int. Conf. Power Energy, Environ. Intell. Control (PEEIC)*, Apr. 2018, pp. 173–177.
[145] S. Vasudevan, "Combining the functionality of multiple automatic cells by introducing a dual-arm robot station," Ph.D. dissertation, Fac. Eng. Natural Sci., Tampere Univ., Tampere, Finland, 2019. [Online]. Available: https://trepo.tuni.fi/handle/10024/117798
[146] B. Muhammedali, M. Z. Abdullah, and M. N. M. Azemi, "Food handling and packaging using computer vision and robot," in *Proc. Int. Conf. Comput. Graph., Imag. Visualizat. (CGIV)*, vol. 51, 2004, pp. 177–182.
[147] F. Bader and S. Rahimifard, "A methodology for the selection of industrial robots in food handling," *Innov. Food Sci. Emerg. Technol.*, vol. 64, Aug. 2020, Art. no. 102379.
[148] *FANUC SCARA—Productivity At the Highest Level*. Accessed: Feb. 15, 2024. [Online]. Available: https://scara.fanuc.eu/en
[149] H. Liu, X. Lai, and W. Wu, "Time-optimal and jerk-continuous trajectory planning for robot manipulators with kinematic constraints," *Robot. Comput.-Integr. Manuf.*, vol. 29, no. 2, pp. 309–317, Apr. 2013.
[150] Z. Li, G. Li, Y. Sun, G. Jiang, J. Kong, and H. Liu, "Development of articulated robot trajectory planning," *Int. J. Comput. Sci. Math.*, vol. 8, no. 1, p. 52, 2017.
[151] S. Joshi, X. Chu, K. Ramani, K. Thurow, and H. Fleischer, "Application of a dual arm robot for automated sample preparation for cholesterol determination in biliary stent incrustations," in *Proc. IEEE Int. Instrum. Meas. Technol. Conf. (I2MTC)*, May 2018, pp. 1–6.
[152] P. M. Fresnillo, S. Vasudevan, and W. M. Mohammed, "An approach for the bimanual manipulation of a deformable linear object using a dual-arm industrial robot: Cable routing use case," in *Proc. IEEE 5th Int. Conf. Ind. Cyber-Physical Syst. (ICPS)*, May 2022, pp. 1–8.
[153] K. Takata, T. Kiyokawa, I. G. Ramirez-Alpizar, N. Yamanobe, W. Wan, and K. Harada, "Efficient task/motion planning for a dual-arm robot from language instructions and cooking images," in *Proc. IEEE/RSJ Int. Conf. Intell. Robots Syst. (IROS)*, Oct. 2022, pp. 12058–12065.
[154] X. Mu, Y. Xue, and Y.-B. Jia, "Robotic cutting: Mechanics and control of knife motion," in *Proc. Int. Conf. Robot. Autom. (ICRA)*, May 2019, pp. 3066–3072.
[155] *IRB 1200 | ABB Robotics*. Accessed: Feb. 21, 2024. [Online]. Available: https://new.abb.com/products/robotics/robots/articulated-robots/irb-1200-hygienic
[156] M. Wu, J. Mei, Y. Zhao, and W. Niu, "Vibration reduction of delta robot based on trajectory planning," *Mechanism Mach. Theory*, vol. 153, Nov. 2020, Art. no. 104004.
[157] *KUKA AG*. Accessed: Feb. 21, 2024. [Online]. Available: https://www.kuka.com/en-de/products/robot-systems/industrial-robots/kr-delta-robot-hm
[158] T. B. V. Marchtwenty. (Feb. 2024). *Cartesian Robots & Gantry Robots—Midwest Engineered Systems*. [Online]. Available: https://www.mwes.com/types-of-industrial-robots/cartesian-gantry-rectilinear-robots
[159] *M-Line Pre-Cutter and Belly Opener (MPB)*. Accessed: Feb. 22, 2024. [Online]. Available: https://marel.com/en/products/m-line-pre-cutter-and-belly-opener-mpb
[160] *Gantry Robots in the Food and Beverage Industry | Schaeffler Medias*. Accessed: Feb. 22, 2024. [Online]. Available: https://medias.schaeffler.co.uk/en/food-packaging/gantry-robots
[161] (Jun. 2022). *Fanuc DR-3iB STAINLESS*. Accessed: Feb. 22, 2024. [Online]. Available: https://www.fanucamerica.com/products/robots/series/dr-3ib-series-delta-robots/dr-3ib-6-stainless
[162] Schubert Group. *Pick & Place Robots From Schubert for the Best Possible Product Handling | Schubert Group*. Accessed: Feb. 22, 2024. [Online]. Available: https://www.schubert.group/en/packaging-solution/pick-and-place-robots
[163] European Commission. (2022). *Good Performance of EU Agri-food Trade in 2022 Despite Challenges*. [Online]. Available: https://agriculture.ec.europa.eu/news/good-performance-eu-agri-food-trade-2022-despite-challenges-2023-04-13_en
[164] M. Ronzoni, R. Accorsi, L. Botti, and R. Manzini, "A support-design framework for cooperative robots systems in labor-intensive manufacturing processes," *J. Manuf. Syst.*, vol. 61, pp. 646–657, Oct. 2021.
[165] *Robotic Solutions for Food and Beverage | ABB Robotics*. Accessed: Aug. 30, 2024. [Online]. Available: https://new.abb.com/products/robotics/industries/food-and-beverage
[166] (Jan. 2022). *Food Robotics—Food & Beverage Industry Robots*. Accessed: Aug. 30, 2024. [Online]. Available: https://www.fanucamerica.com/solutions/industries/food-robotics-and-beverage-robotics#FOL
[167] *Omron Europe BV*. Accessed: Aug. 30, 2024. [Online]. Available: https://industrial.omron.eu/en/products/fixed-robots
[168] *Food and Beverage*. Accessed: Aug. 30, 2024. [Online]. Available: https://www.motoman.com/en-us/campaign/food-and-beverage
[169] D. Butler, L. Holloway, and C. Bear, "The impact of technological change in dairy farming: Robotic milking systems and the changing role of the stockperson," *J. Roy. Agricult. Soc. England*, vol. 173, no. 622, p. 1, 2012.
[170] (2023). *GEA DairyRobot R9500 Milking Robot | Intelligent Automatic Milking*. [Online]. Available: https://www.gea.com/en/products/milking-farming-barn/dairyrobot-automated-milking/dairyrobot-r9500-robotic-milking-system.jsp
[171] B. K. Panda, S. S. Panigrahi, G. Mishra, and V. Kumar, "Robotics for general material handling machines in food plants," in *Transporting Operations of Food Materials Within Food Factories*. Amsterdam, The Netherlands: Elsevier, 2023, pp. 341–372.
[172] (2024). *Scott Automation: Beef Processing Solutions*. Accessed: Feb. 28, 2024. [Online]. Available: https://scott.co.nz/en-gb/products/meat/beef
[173] A. Mason, D. Romanov, L. E. Cordova-Lopez, and O. Korostynska, "Smart knife: Integrated intelligence for robotic meat cutting," *IEEE Sensors J.*, vol. 22, no. 21, pp. 20475–20483, Nov. 2022.
[174] E. Bar, J. R. Mathiassen, A. Eilertsen, T. Mugaas, E. Misimi, Å. S. Linnerud, C. Salomonsen, and H. Westavik, "Towards robotic post-trimming of salmon fillets," *Ind. Robot: Int. J.*, vol. 43, no. 4, pp. 421–428, Jun. 2016.
[175] A.-P. Hu, J. Bailey, M. Matthews, G. McMurray, and W. Daley, "Intelligent automation of bird deboning," in *Proc. IEEE/ASME Int. Conf. Adv. Intell. Mechtron. (AIM)*, Aug. 2012, pp. 286–291.
[176] G. J. Monkman, S. Hesse, R. Steinmann, and H. Schunk, *Robot Grippers*. Hoboken, NJ, USA: Wiley, 2007.
[177] R. Mykhailyshyn, V. Savkiv, P. Maruschak, and J. Xiao, "A systematic review on pneumatic gripping devices for industrial robots," *Transport*, vol. 37, no. 3, pp. 201–231, Aug. 2022.
[178] Z. Wang, S. Hirai, and S. Kawamura, "Challenges and opportunities in robotic food handling: A review," *Frontiers Robot. AI*, vol. 8, Jan. 2022, Art. no. 789107.
[179] J. Hernandez, M. S. H. Sunny, J. Sanjuan, I. Rulik, M. I. I. Zarif, S. I. Ahamed, H. U. Ahmed, and M. H. Rahman, "Current designs of robotic arm grippers: A comprehensive systematic review," *Robotics*, vol. 12, no. 1, p. 5, Jan. 2023.
[180] Y. Liu, J. Hou, C. Li, and X. Wang, "Intelligent soft robotic grippers for agricultural and food product handling: A brief review with a focus on design and control," *Adv. Intell. Syst.*, vol. 5, no. 12, Dec. 2023, Art. no. 2300233.
[181] D. J. Sut and P. Sethuramalingam, "Soft manipulator for soft robotic applications: A review," *J. Intell. Robotic Syst.*, vol. 108, no. 1, p. 10, May 2023.
[182] J. F. Elfferich, D. Dodou, and C. D. Santina, "Soft robotic grippers for crop handling or harvesting: A review," *IEEE Access*, vol. 10, pp. 75428–75443, 2022.

[183] E. Vrochidou, V. N. Tsakalidou, I. Kalathas, T. Gkrimpizis, T. Pachidis, and V. G. Kaburlasos, "An overview of end effectors in agricultural robotic harvesting systems," *Agriculture*, vol. 12, no. 8, p. 1240, Aug. 2022.

[184] W. Mandil, V. Rajendran, K. Nazari, and A. Ghalamzan-Esfahani, "Tactile-sensing technologies: Trends, challenges and outlook in agri-food manipulation," *Sensors*, vol. 23, no. 17, p. 7362, Aug. 2023.

[185] B. J. Mulholland, P. S. Panesar, and P. H. Johnson, "The adoption of robotics in pack houses for fresh produce handling," *J. Horticultural Sci. Biotechnol.*, vol. 99, no. 1, pp. 9–19, Jan. 2024.

[186] Y. Xin, X. Zhou, H. Bark, and P. S. Lee, "The role of 3D printing technologies in soft grippers," *Adv. Mater.*, vol. 36, no. 34, Aug. 2024, Art. no. 2307963.

[187] C. Blanes, M. Mellado, and P. Beltran, "Novel additive manufacturing pneumatic actuators and mechanisms for food handling grippers," *Actuators*, vol. 3, no. 3, pp. 205–225, Jul. 2014.

[188] *Marel Robobatcher Flex 3D Printed*. Accessed: Feb. 13, 2024. [Online]. Available: https://marel.com/en/news/robobatcher-gets-a-firm-grip-on-styling/

[189] *Automatics and Industrial Informatics Research Institute*. Accessed: Feb. 13, 2024. [Online]. Available: https://www.ai2.upv.es/

[190] *Suction Cup Gripper for Salmon Handling of Gripwiq*. Accessed: Feb. 13, 2024. [Online]. Available: https://gripwiq.com/cases/suction-gripper-for-salmon-handling/

[191] *Underactuated Mechanical Gripper*. Accessed: Feb. 13, 2024. [Online]. Available: https://youtu.be/iY4qnVuzlck?si=7zkprzhIVDkM1VaU

[192] *Pisoftgrip Grippers of Piab*. Accessed: Feb. 13, 2024. [Online]. Available: https://www.piab.com/en-us/suction-cups-and-soft-grippers/soft-grippers/pisoftgrip-vacuum-driven-soft-gripper-/sg.x/

[193] *Soft Fingers Gripper of Softgripping Gmbh*. Accessed: Feb. 13, 2024. [Online]. Available: https://soft-gripping.com/

[194] R. A. Kulwiec, "Basic materials handling concepts," in *Materials Handling Handbook*. Hoboken, NJ, USA: Wiley, 1985, pp. 1–18.

[195] M. Rao, "Transport and storage of food products," in *Handbook of Food Engineering*. Boca Raton, FL, USA: CRC Press, 2018, pp. 551–596.

[196] P. J. Fellows, "Chapter 25—Materials handling, storage and distribution," in *Food Processing Technology* (Woodhead Publishing Series in Food Science, Technology and Nutrition), 5th ed. P. J. Fellows, Ed., Sawston, U.K.: Woodhead, 2022, pp. 739–751. [Online]. Available: https://www.sciencedirect.com/science/article/pii/B9780323857376000066

[197] *Ford: The Moving Assembly Line and the Five-dollar Workday*. Accessed: Feb. 23, 2024. [Online]. Available: https://corporate.ford.com/articles/history/moving-assembly-line.html

[198] (2005). *EHEDG: Doc. 32 Materials of Construction for Equipment in Contact With Food*. [Online]. Available: https://www.ehedg.org/guidelines-working-groups/guidelines/guidelines/detail/materials-of-construction-for-equipment-in-contact-with-food

[199] J. Kold and C. Silverman, "Conveyors used in the food industry," in *Handbook of Hygiene Control in the Food Industry*. Amsterdam, The Netherlands: Elsevier, 2016, pp. 367–382.

[200] *Food Grade Conveyor Belts—Dorner Conveyors*. Accessed: Feb. 22, 2024. [Online]. Available: https://www.dornerconveyors.com/europe/industries/food-handling-and-processing

[201] *Positive Drive—Volta Belting*. Accessed: Feb. 22, 2024. [Online]. Available: https://www.voltabelting.com/positive-drive

[202] *Straight Conveyors | Global Manufacturer | Wire Belt U.K.*. Accessed: Feb. 22, 2024. [Online]. Available: https://wirebelt.co.uk/products/conveyors/straight-conveyors

[203] *Intralox: Modular Plastic Belting Tools and Components*. Accessed: Feb. 22, 2024. [Online]. Available: https://www.intralox.com/products/modular-plastic-belting/tools-and-components

[204] *Ammeraal Beltech: Round & V-belts*. Accessed: Feb. 22, 2024. [Online]. Available: https://www.ammeraalbeltech.com/en/products/round-and-v-belts

[205] E. M. Sloot and N. P. Kruyt, "Theoretical and experimental study of the transport of granular materials by inclined vibratory conveyors," *Powder Technol.*, vol. 87, no. 3, pp. 203–210, Jun. 1996.

[206] M. E. F. Skocir and S. Thomas, "Vibratory conveyors," in *Mechanical Conveyors*. Evanston, IL, USA: Routledge, 1997, p. 46.

[207] S. Keppler, S. Bakalis, C. E. Leadley, and P. J. Fryer, "Processing of barley grains in a continuous vibrating conveyor," *J. Food Eng.*, vol. 187, pp. 114–123, Oct. 2016.

[208] T. Hill, "A study of vibratory conveyors and feeders," *Steel Times*, vol. 206, no. 11, p. 970, 1978.

[209] J. M. Boac, R. P. K. Ambrose, M. E. Casada, R. G. Maghirang, and D. E. Maier, "Applications of discrete element method in modeling of grain postharvest operations," *Food Eng. Rev.*, vol. 6, no. 4, pp. 128–149, Dec. 2014.

[210] T. O. Olanrewaju, "Design and fabrication of a screw conveyor," *Agricult. Eng. Int., CIGR J.*, vol. 19, no. 3, pp. 156–162, 2017.

[211] N. Kumar, "Chapter Eight—Fundamentals of conveyors," in *Transporting Operations of Food Materials Within Food Factories*, S. M. Jafari and N. Malekjani, Eds., Sawston, U.K.: Woodhead, Jan. 2023, pp. 221–251. [Online]. Available: https://www.sciencedirect.com/science/article/pii/B9780128185858000039

[212] (Jul. 2023). *Laitex Screw Conveyors for Demanding Processing Conditions*. Accessed: Feb. 23, 2024. [Online]. Available: https://www.laitex.fi/product/screw-conveyors

[213] *Delfin Pneumatic Conveying Solutions: Dense Phase and Dilute Phase Pneumatic Conveyors*. Accessed: Feb. 23, 2024. [Online]. Available: https://www.delfinconveyors.com/en/pneumatic-conveyors

[214] D. Mills, *Pneumatic Conveying Design Guide*. Oxford, U.K.: Butterworth-Heinemann, Oct. 2013.

[215] D. McGlinchey, *Bulk Solids Handling: Equipment Selection and Operation*. Chichester, U.K.: Blackwell, Apr. 2008.

[216] P. Miller, S. Wirasinghe, L. Kattan, and A. de Barros, "Monorails for sustainable transportation—A review," *Gen*, vol. 181, no. 1, pp. 1–13, 2014.

[217] I. Syed, H. K. Kommineni, S. S. Sunkara, and I. B. Abdul, "Hydraulic conveyors, bucket conveyors, and monorails," in *Transporting Operations of Food Materials Within Food Factories*. Amsterdam, The Netherlands: Elsevier, 2023, pp. 293–313.

[218] *Small Feeders | Volumetric Feeders | Gravimetric Feeders*. Accessed: Feb. 22, 2024. [Online]. Available: https://www.tinsleycompany.com/equipment-systems/small-feeders

[219] *Indpro: Pneumatic Conveying System | Vacuum Conveying System*. Accessed: Feb. 22, 2024. [Online]. Available: https://www.indpro.com/pneumatic-conveying-system.html

[220] *Mezbaha Teknolojileri: Cold Room Monorail and Twinrail*. Accessed: Feb. 22, 2024. [Online]. Available: https://www.mezbahateknolojileri.com/en/cold-room-monorail-and-twinrail

[221] PAP Limited. (Feb. 2024). *Product| Manufacturer of Industrial Conveyor Systems—Promech Automation*. [Online]. Available: http://promechautomation.com/Home/Power-Roller-Conveyor/Screw-Food-Roller-Conveyor-11

[222] G. D. Saravacos, A. E. Kostaropoulos, G. D. Saravacos, and A. E. Kostaropoulos, "Mechanical transport and storage equipment," in *Handbook of Food Processing Equipment*. New York, NY, USA: Kluwer, 2002, pp. 78–133.

[223] SB Machinery. (May 2023). *Fruit Elevator and Conveyor Introduction*. IBC Machine. [Online]. Available: https://fruitprocessingmachine.com/fruit-and-vegetable-elevator-and-conveyor-introduction

[224] E. Alehosseini, Z. Mohammadi, and S. M. Jafari, "Introduction to unit operations and process description in the food industry," in *Engineering Principles of Unit Operations in Food Processing*. Amsterdam, The Netherlands: Elsevier, 2021, pp. 1–27.

[225] *Hydraulic Conveyor By Agromeccanica SRl | DirectIndustry*. Accessed: Feb. 23, 2024. [Online]. Available: https://www.directindustry.com/prod/agromeccanica-srl/product-209615-2133297.html

[226] *Conveyor Systems—Food Industry Machinery | Martak*. Accessed: Feb. 23, 2024. [Online]. Available: https://martak.com/equipment-and-services-for-shrimp-and-fish-industry/conveyor-systems

[227] P. Fellows, "Chapter 2—Raw material preparation," in *Food Processing Technology* (Woodhead Publishing Series in Food Science, Technology and Nutrition), 5th ed., P. Fellows, Ed., Sawston, U.K.: Woodhead, 2022, pp. 99–112. [Online]. Available: https://www.sciencedirect.com/science/article/pii/B9780323857376000108

[228] *Egg Grading | World Leading Manufacturer | MOBA*. Accessed: Feb. 23, 2024. [Online]. Available: https://www.moba.net/page/en/Products/Grading

[229] A. Sakudo and Y. Yagyu, "Application of a roller conveyor type plasma disinfection device with fungus-contaminated citrus fruits," *AMB Exp.*, vol. 11, no. 1, pp. 1–8, Dec. 2021.
[230] (Dec. 2021). *Multiscan S90 Citrus Sorter | MULTISCAN*. Accessed: Feb. 23, 2024. [Online]. Available: https://multiscan.eu/en/multiscan-technologies-launches-the-new-multiscan-s90-citrus-sorter
[231] M. Kaur, H. K. Sharma, and N. Kumar, "Processing of oilseeds," in *Agro-Processing and Food Engineering: Operational and Application Aspects*. Cham, Switzerland: Springer, 2022, pp. 483–533.
[232] *Oilseeds Screw Presses Small Capacities—UNO, DUO | Farmet*. Accessed: Feb. 23, 2024. [Online]. Available: https://www.farmet.cz/en/oilseeds-screw-presses-uno-duo
[233] M. M. El-Kholy and R. M. Kamel, "Development and evaluation of an innovative grain cart with a pneumatic conveyor," *Heliyon*, vol. 7, no. 11, Nov. 2021, Art. no. e08461.
[234] *Pneumatic Conveyor for Raw Coffee, Roaster Loading*. Accessed: Feb. 29, 2024. [Online]. Available: https://www.delfinconveyors.com/en/pneumatic-conveying-in-the-food-industry/pneumatic-conveyor-for-raw-coffee-roaster-loading
[235] *Coffee Packaging Machine Feeding*. Accessed: Feb. 29, 2024. [Online]. Available: https://www.delfinconveyors.com/en/pneumatic-conveying-in-the-food-industry/pneumatic-conveyor-for-coffee-packaging-machine-feeding
[236] *ISA95, Enterprise-Control System Integration–ISA*. Accessed: Aug. 27, 2024. [Online]. Available: https://www.isa.org/standards-and-publications/isa-standards/isa-standards-committees/isa95
[237] P. M. Fresnillo, S. Vasudevan, J. A. Perez Garcia, and J. L. Martinez Lastra, "An open and reconfigurable user interface to manage complex ROS-based robotic systems," *IEEE Access*, vol. 12, pp. 114601–114617, 2024.
[238] D. Beric, S. Havzi, T. Lolic, N. Simeunovic, and D. Stefanovic, "Development of the MES software and integration with an existing ERP software in industrial enterprise," in *Proc. 19th Int. Symp. INFOTEH-JAHORINA (INFOTEH)*, Mar. 2020, pp. 1–6.
[239] M. Shaikh, P. Shah, and R. Sekhar, "Communication protocols in industry 4.0," in *Proc. Int. Conf. Sustain. Emerg. Innov. Eng. Technol. (ICSEIET)*, vol. 40, Sep. 2023, pp. 709–714.
[240] F.-L. Lian, J. R. Moyne, and D. M. Tilbury, "Performance evaluation of control networks: Ethernet, ControlNet, and DeviceNet," *IEEE Control Syst. Mag.*, vol. 21, no. 1, pp. 66–83, Feb. 2001.
[241] (Jan. 2020). *Search Rockwell Automation*. Accessed: Aug. 28, 2024. [Online]. Available: https://tinyurl.com/4ba6rs47
[242] *What is DDS?*. Accessed: Aug. 28, 2024. [Online]. Available: https://www.dds-foundation.org/what-is-dds-3
[243] *EtherCAT*, Beckhoff Automation GmbH, Co. KG, Hülshorstweg, Verl, Germany, Accessed: Aug. 28, 2024. [Online]. Available: https://www.beckhoff.com/en-en/products/io/ethercat
[244] EtherCAT Technology Group. *EtherCAT Technology Group | EtherCAT*. Accessed: Aug. 28, 2024. [Online]. Available: https://www.ethercat.org/en/technology.html
[245] FieldComm Group. *FOUNDATION Fieldbus Technical Specifications*. Accessed: Aug. 28, 2024. [Online]. Available: https://www.fieldcommgroup.org/foundation-fieldbus-technical-specifications#230548828-3045326808
[246] J. Jasperneite, "Interbus," in *Industrial Communication Technology Handbook*. Boca Raton, FL, USA: CRC Press, Dec. 2017, pp. 1–15.
[247] *System overview Interbus*, Beckhoff Automation GmbH, Co. KG, Hülshorstweg, Verl, Germany, Accessed: 28, Aug. 2024. [Online]. Available: https://www.beckhoff.com/fifi/products/i-o/overview-fieldbus-systems/interbus
[248] R. Heynicke, D. Krush, C. Cammin, G. Scholl, B. Kaercher, J. Ritter, P. Gaggero, and M. Rentschler, "IO-link wireless enhanced factory automation communication for industry 4.0 applications," *J. Sensors Sensor Syst.*, vol. 7, no. 1, pp. 131–142, Mar. 2018.
[249] *IO-Link Im Durchblick*. Accessed: Aug. 28, 2024. [Online]. Available: https://io-link.com/en/Technology/what_is_IO-Link.php?thisID=76
[250] *Modbus Specifications and Implementation Guides*. Accessed: Aug. 28, 2024. [Online]. Available: https://www.modbus.org/specs.php
[251] G. Thomas, "Introduction to the Modbus protocol," *Extension*, vol. 9, no. 4, pp. 1–4, 2008.
[252] *MQTT—The Standard for IoT Messaging*. Accessed: Aug. 28, 2024. [Online]. Available: https://mqtt.org
[253] M. B. Yassein, M. Q. Shatnawi, S. Aljwarneh, and R. Al-Hatmi, "Internet of Things: Survey and open issues of MQTT protocol," in *Proc. Int. Conf. Eng. MIS (ICEMIS)*, May 2017, pp. 1–6.
[254] (Sep. 2019). *Unified Architecture—OPC Foundation*. Accessed: Aug. 28, 2024. [Online]. Available: https://opcfoundation.org/about/opc-technologies/opc-ua
[255] Industry Support Siemens. *OPC UA—An Overview of the Most Important Entries and Links—ID: 109770435*. Accessed: Aug. 28, 2024. [Online]. Available: https://tinyurl.com/5n93rfsz
[256] *PROFINET–Technology Description*. Accessed: Aug. 28, 2024. [Online]. Available: https://www.profinet.com/profinet-explained/technology-description
[257] G. Prytz, "A performance analysis of EtherCAT and PROFINET IRT," in *Proc. IEEE Int. Conf. Emerg. Technol. Factory Autom.*, Sep. 2008, pp. 15–18.
[258] J. Sonnenberg, "Serial communications Rs232, Rs485, Rs422," Raveon Technol. Corp, Cousteau, CA, USA, Tech. Rep. AN236 Rev D2, 2018.
[259] *AIX 7.1*. Accessed: Aug. 28, 2024. [Online]. Available: https://www.ibm.com/docs/zh-tw/aix/7.1?topic=protocol-tcpip-protocols
[260] C. M. Kozierok, *The TCP/IP Guide: A Comprehensive, Illustrated Internet Protocols Reference*. San Francisco, CA, USA: No Starch Press, 2005.
[261] H. A. Alobaidy, J. Mandeep, R. Nordin, and N. F. Abdullah, "A review on ZigBee based WSNs: concepts, infrastructure, applications, and challenges," *Int. J. Electr. Electron. Eng. Telecommun.*, vol. 9, no. 3, pp. 189–198, 2020.
[262] S. Ding, J. Liu, and M. Yue, "The use of ZigBee wireless communication technology in industrial automation control," *Wireless Commun. Mobile Comput.*, vol. 2021, no. 1, Jan. 2021, Art. no. 8317862.
[263] *Multiscan Technologies*. Accessed: Sep. 6, 2024. [Online]. Available: https://multiscan.eu/en/
[264] Marumi Food Co. *Marumi Food Co*. Accessed: Aug. 30, 2024. [Online]. Available: https://marumifood.amebaownd.com
[265] *RS020N | Industrial Robots By Kawasaki Robotics*. Accessed: Aug. 30, 2024. [Online]. Available: https://kawasakirobotics.com/asia-oceania/products-robots/rs020n
[266] Case Study Marumi Foods Co. Ltd.'s (Jul. 2024). *Frozen Food Boxing-Boxing-Automating Boxing | Industrial Robots by Kawasaki Robotics*. Accessed: Aug. 30, 2024. [Online]. Available: https://kawasakirobotics.com/asia-oceania/case-studies/case_marumifoods

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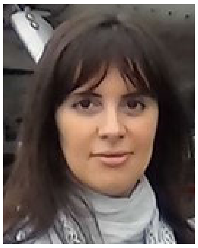

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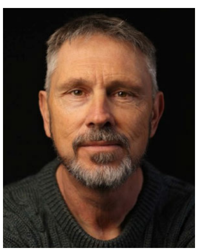

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