

## Review

# Meat 4.0: Principles and Applications of Industry 4.0 Technologies in the Meat Industry

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**Abstract:** Meat 4.0 refers to the application the fourth industrial revolution (Industry 4.0) technologies in the meat sector. Industry 4.0 components, such as robotics, Internet of Things, Big Data, augmented reality, cybersecurity, and blockchain, have recently transformed many industrial and manufacturing sectors, including agri-food sectors, such as the meat industry. The need for digitalised and automated solutions throughout the whole food supply chain has increased remarkably during the COVID-19 pandemic. This review will introduce the concept of Meat 4.0, highlight its main enablers, and provide an updated overview of recent developments and applications of Industry 4.0 innovations and advanced techniques in digital transformation and process automation of the meat industry. A particular focus will be put on the role of Meat 4.0 enablers in meat processing, preservation and analyses of quality, safety and authenticity. Our literature review shows that Industry 4.0 has significant potential to improve the way meat is processed, preserved, and analysed, reduce food waste and loss, develop safe meat products of high quality, and prevent meat fraud. Despite the current challenges, growing literature shows that the meat sector can be highly automated using smart technologies, such as robots and smart sensors based on spectroscopy and imaging technology.

**Keywords:** authenticity; automation; digitalisation; fourth industrial revolution; meat; quality; robotics; safety; smart sensors; spectroscopy

## 1. Introduction

The world population is increasing rapidly and it is expected to hit approximately 10 billion people by the year 2050. Ensuring enough, safe, and sustainable food for all of these people remains one of the key future challenges facing humanity, especially in the current scenario of resource depletion, pandemics, and climate change [1–3]. Meat production and consumption have increased over the past five decades and it is expected that the meat production will continue increasing in order to meet the growing demand for animal proteins [4,5]. However, due to their high perishability, various preservation and processing methods have been traditionally applied to meat and meat products to maintain

high quality and extend their shelf life [6,7]. On the other hand, a wide range of analytical methods has been investigated over the years to characterize meat and meat products in terms of quality, safety, and authenticity. Yet, many of the conventional preservation, processing, and analytical methods are unable to cope with the well-known challenges (e.g., short shelf life and large heterogeneity) faced by the meat industry, making it difficult to preserve, process, and analyse these products [8–12].

In recent years, new innovations and the development of a new wave of advanced technologies have revolutionized food systems and the food industry [13–15]. These advancements have been accelerated by the advent of many emerging technologies under the context of the fourth industrial revolution (called Industry 4.0 or IR 4.0), which has digitally transformed many food manufacturing sectors, including the meat industry. Indeed, as other industries, the meat industry has experienced a significant transformation during the ongoing industrial revolution [5,16].

Before Industry 4.0, three industrial revolutions took place, allowing significant improvements and technological advances to be implemented in various agricultural and industrial sectors. The first industrial revolution (IR 1.0) occurred in the late eighteenth century, and was characterized by the transition from manual to mechanized work and production, which were powered by steam. The second one (IR 2.0) dates back to the late nineteenth century, and was marked by the first use of electrical power to create mass production. The third industrial revolution (IR 3.0) began in the early 1970s with the arrival of electronics and information technology, leading to automated production [17–19].

Industry 4.0 has become an interdisciplinary topic, involving a set of knowledge and technologies related to physical, digital, and biological domains [20–22]. Although no general agreement exists in the literature on the Industry 4.0 enablers, the most reported technologies in the food industry are Artificial Intelligence (AI), Big Data (BD), robotics, smart sensors, the Internet of Things (IoT), augmented reality, cybersecurity, and blockchain [14,23,24]. The interest in Industry 4.0 has gained momentum recently, especially after 2015, which has been reflected by the increased number of publications (and the corresponding citations) dealing with this topic, as can be noticed from Figure 1.

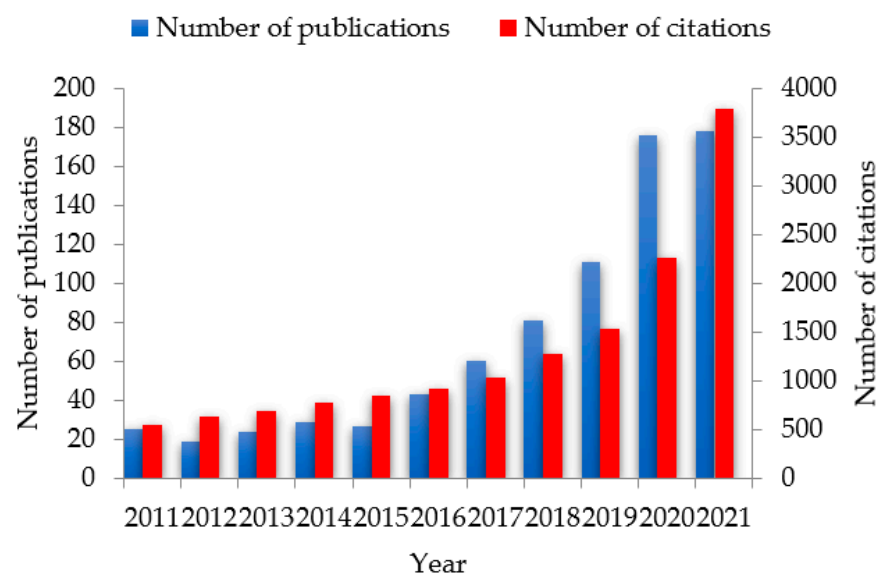


**Figure 1.** Number of publications and citations per year (search query was performed on 18 May 2022) on application of Industry 4.0 in the food industry over the last decade. The following keyword search query was used in Scopus: TITLE-ABS-KEY (Fourth industrial revolution) OR (Industry 4.0) AND (Food industry).

This increased interest in Industry 4.0 can be explained by its ability to digitalize the food industry by using smart interconnected technologies and web-based platforms [14].

Several publications have indicated that Industry 4.0 and its technologies have the potential to promote more automation and digitalization, leading to the concept of a smart factory, with improved efficiency, higher food quality, reduced food loss, and reduced production cost and time [5,25]. Moreover, worker shortages and other disruptions caused by the COVID-19 pandemic have accelerated the move toward more automation and digitalization over the last few years [15,26,27].

Many Industry 4.0 components, such as AI [25], BD [3], robotics [28,29], IoT [30], and augmented reality (AR) [31], have been reviewed in recent years. In the meat industry, it was reported that the application of AI decreases costs by optimizing operations and improves profitability in meat processing plants [16]. An overview of recent developments and advances in human–robot collaboration in the red meat industry was given by Romanov et al. [32]. The application of AR in slaughterhouses seemingly increases the production yield [33]. Recently, the application of Industry 4.0 technologies in seafood preservation, processing, and analytical methods was also reviewed [23].

This review will report on recent advances and technological developments in the meat industry focusing on Industry 4.0 technologies. The application of Industry 4.0 elements in meat preservation, processing, and analysis will be termed “Meat 4.0”. More concretely, examples on the use of AI, BD, robotics, smart sensors, and blockchain, among other Industry 4.0 components to ensure higher quality, safety, and traceability in the meat industry, will be presented.

## 2. Principles of Industry 4.0 from Food Perspectives and Meat 4.0 Concept

### 2.1. Meat 4.0 Concept

After twenty-five decades of industrial advances, we are currently in the era of cyber-physical systems, i.e., a computerized system in which functions are controlled or monitored through computer-based algorithms [24]. Figure 2 shows the meat supply chain and the key Industry 4.0 technologies that are being adopted at each actor level. There are technologies such as cybersecurity and blockchain that are being implemented throughout the meat supply chain. Therefore, the application of these Industry 4.0 technologies to the meat supply chain can be termed as “Meat 4.0”.

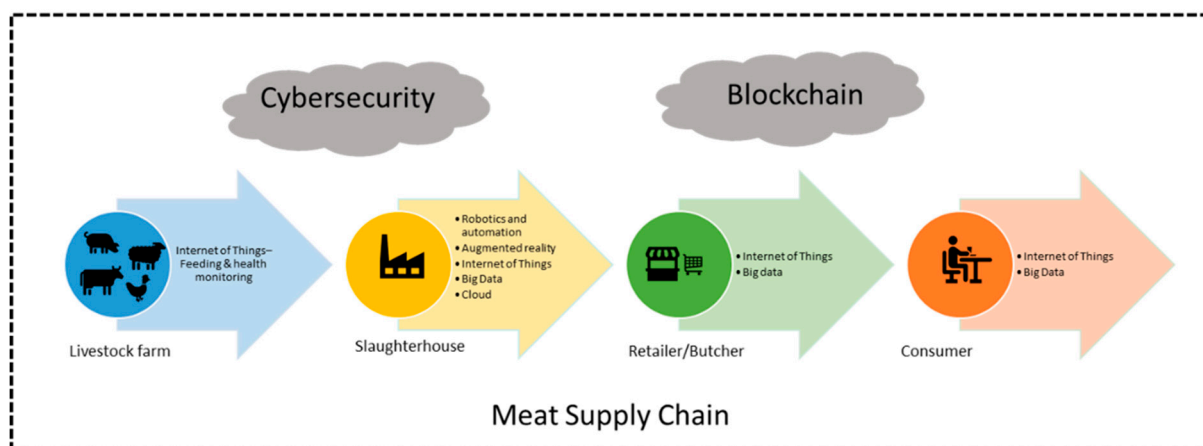


**Figure 2.** Meat 4.0—Application of Industry 4.0 technologies in the meat supply chain.

### 2.2. Food Industry 4.0 Enablers

This section will discuss each of the key technologies mentioned in with respect to the meat sector.

#### 2.2.1. Robotics and Automation

Industrial robots and automation make up an important component of Industry 4.0, which could resolve some challenges in the food industry, such as the difficulty of obtaining

adequate labour and reducing production time and processing costs [24]. Traditionally, automating meat factories has been very challenging because of the huge initial costs involved and carcasses coming in various sizes, making it hard for robots to maintain consistency during cutting processes [29]. However, the advent of the COVID-19 pandemic forced many meat factories to close down temporarily due to safety concerns among its employees. Yet, at the same time, it accelerated their plans to automate the factories [27]. Processes such as cutting, deboning, and shredding of meats such as beef, lamb, pork, and poultry, which were completely dependent on hand skills of the workforce, are now carried out using robots and automation. Manufacturers have benefitted through decreased cycle times and increased throughput. It means that meat products reach customers faster, reducing spoilage and giving the products the best shelf life possible. Also, less human contact with processes and products has reduced staff injuries and product contamination. Figure 3 shows some robotics and automation within the meat sector.



**Figure 3.** Robotics and automation in the meat sector ((a) bovine hindquarter cut; (b) lamb ventral cut; (c,d) automated poultry line).

#### 2.2.2. Big Data (BD)

BD is associated with unstructured data of different types, which are generated continuously at high speed and in large volumes. Furthermore, BD are characterized by being data with high veracity and value [34]. In the meat supply chain, BD is generated mainly through sensors. Concretely, these sensors generate data related to physiological or behavioural parameters of livestock [35]. For instance, various data related to animal behaviour such as resting, ruminating, feeding, and walking habits can be analysed, and trends related to their health can be obtained [36]. BD can also provide supports with feed and disease management. There is a great potential to utilize the BD to improve the operational efficiency of the meat supply chain [3]. BD can also be used to predict outcomes related to body weight, yield and production, creating new efficiencies and greater economic benefits [37]. It can help in understanding the market and consumer trends and develop new products and services [38].

#### 2.2.3. Internet of Things

IoT is related to transferring data between interconnected computer devices and machinery [24]. It consists of physical devices that collect data, a network that transmits the collected data, and an application layer which includes IoT applications and services.

Thus, IoT has favoured the spread of interconnected devices fostering an increase in the employ of several smart IoT applications [39]. Moreover, IoT is widely applied in the supply chain to enhance transparency and traceability [30]. The horsemeat scandal in 2013 was caused when several adulterated meat products were identified, resulting in the public losing trust in them [40]. IoT-enabled wearable devices allow real-time monitoring and tracking, employee safety, productivity, and food safety [41]. For instance, the use of hyperspectral imaging systems in combination with IoT could help to monitor the components/ingredients of food, thus improving food safety [42]. Some researchers used IoT technology to reduce food waste in food processing factories [43,44].

#### 2.2.4. Augmented Reality (AR)

Augmented reality allows to improve the visual perception of the real world [33]. The application of augmented reality to the carcasses cutting operation has resulted in an increase in the production yield; however, the staff require training in order to benefit fully from the efficiency and capability of the AR application rather than implementing the standard procedure of verbal communication of instructions [33]. The AR platform, called ARGA (Augmented Reality Grading App), enables faster, more consistent, and more accurate meat grading while taking full advantage of the experience and capabilities of the industry's meat graders [45]. It is widely used in training of the staff as well as guiding step-by-step maintenance or operating procedures [31].

#### 2.2.5. Cybersecurity

Cybersecurity concerns the processes and availability of technologists with the needed skills that protect information and computer technology systems, such as networks and computers [24]. Cyberattacks have been steadily rising globally and affected several industries and manufacturing sectors, including businesses, schools, hospitals, governmental websites, etc., [46]. Whenever a new technology is adopted or implemented into an industry, cybersecurity becomes a reason of great concern. For instance, JBS, who are one of the largest meat processors in the United States, fell prey to cyberattacks resulting in shortages [47]. Therefore, considering the scale and significance of this sector with regards to food security, it is essential to ensure that meat supply chain IT systems are secured.

#### 2.2.6. Blockchain

The meat supply chain has not been very efficient and has always been a cause of concern when it comes to environmental sustainability [48]. JBS, the largest meat producer, has been accused of deforestation of Amazonian forests for livestock grazing as well as passing off these cattle as legitimate [49]. These issues triggered JBS to implement blockchain technology to ensure traceability of its livestock and meat [50], since blockchain consists of distributed, decentralized, digital ledgers supported by a network of multiple computers. Thus, blockchain technology has the ability to provide market regulators and consumers with increased levels of transparency and confidence in food quality and safety. Several applications of blockchain technology in the meat sector have resulted in raising consumer confidence through tracking technologies, tackling food fraud, non-tampering of data, secure information storage and providing greater levels of trust in meat supply chains [51].

#### 2.2.7. Imaging Technology

Imaging technology is extensively employed in the supply chain to allow visual assessment of foods on the processing line with minimal human intervention. Concretely, these 4.0 techniques permit the integration of systems capable of “seeing” and reacting to different situations based on previously defined parameters. In this way, once the optimum quality criteria have been established for a product, the intelligent systems will be able to act by making instant decisions in the processing line itself [52]. Various imaging technologies exist such as spectral imaging (also known as spectroscopic imaging or chemical

imaging), near-infrared, X-ray imaging, digital and analogue image processing, and odour imaging [53]. These methodologies consist of capturing images in real time, which are displayed on computers and automatically analysed to generate control commands based on the results obtained [54]. Spectral images are one of the most used imaging techniques, among which hyper and multispectral images are distinguished. In the case of hyperspectral images, they collect and process information from the entire electromagnetic spectrum (wavelengths in near-ultraviolet, visible, and near-, mid- and far-infrared) as well as from spatial surface. However, hyperspectral imaging direct use is limited by the extensive time needed to process large volumes of data. For this reason, the selection of characteristic wavelengths is made that allows the development of a multispectral imaging system [55,56]. For its part, near-infrared permits obtaining the spectrum of an object in the wavelength range of 750 to 2500 nm. In this way, multispectral and near-infrared imaging can provide qualitative and/or quantitative information from the interaction of electromagnetic waves with food constituents.

### 3. Industry 4.0 Technologies Applied for Meat Processing and Preservation

The need for sustainable food systems calls for innovative plans that secure the global food supply and minimize food losses and waste throughout the supply chain. Here, the use of IR 4.0 technologies in the processing chain and during meat preservation is of special importance as it could prevent food losses. Among the tools that could help minimize waste and maintain adequate production are robotics and automation IR 4.0 systems, since they favour rapid processing by minimizing sources of contamination, and therefore increasing the shelf life of the meat. However, on account of peculiarity of animal carcasses and the locations obtained from them, robotization and automation processes are a challenge for Meat 4.0. Despite this initial complexity, the development and implementation of robotization and automation are of special interest because the slaughter tasks and the secondary processing of the carcasses are labours that currently involve most of the manual work, which is repetitive and must be done at high speed [32]. Although it is true that in the case of slaughterhouses many processing operations (stunning, bleeding, scalding, plucking, skinning, evisceration, splitting, and cooling) are already successfully automated [57], in the secondary processing of meat, hardware and software must be developed so that robots can offer a flexible, scalable, compact, and profitable alternative in the production line [32].

Cutting and boning operations are among the most labour-intensive due to the skill and sense required during processing. In this field, there are some automation systems that use detection units based on vision scanners in order to define the path and depth of the meat cuts in the primary and secondary meat processing stages (Table 1). On this matter, in automation for cutting, the use of laser lines that allow 3D scanning is common. A very prominent example of automation in the meat industry is the AiRA Robotics set, developed by the Frontmatec Company for employ in the clean line of pork slaughterhouses. Among this set, it is worth highlighting the presence of the robot designed to vacuum and remove the plugs from the carcass rectum (*AiRA RBD Bung Dropper*); the aitch bone cutter (*AiRA RHC Aitch Bone Cutter*); the breast and belly cutter (*AiRA RBO Breast and Belly Opener*); the head clipper (*AiRA RNC Neck Clipper*); and the carcass splitter (*AiRA Splitters*). The technology developed by Frontmatec has both the robot and saw combination (*AiRA RPS-S Splitter with Saw*), as well as a robot and knife (*AiRA RPS-H Splitter with Knives*) and even has a pair of robotic arms (*AiRA RPS-D Dual Arm Splitter with Saw*) [57]. Also in pork meat, there are currently different IR 4.0 technologies that allow deboning (femur and tibia removal) the back legs through robotic systems. *Hamdas-RX* [58] and *SRDViand project* [59] are two of these IR 4.0 technologies, which allow deboning through X-ray and 3D images, respectively, to calculate the cutting path to be followed by the robotic equipment.

**Table 1.** Automation and robotization of the primary and secondary processing of various carcasses in the meat industry.

| Carcass                 | IR 4.0 Technology                                    | Application                                   | Reference |
|-------------------------|------------------------------------------------------|-----------------------------------------------|-----------|
| Pork                    | <i>AiRA RBD Bung Dropper</i> <sup>a</sup>            | Remove plugs from rectum                      | [57]      |
|                         | <i>AiRA RHC Aitch Bone Cutter</i> <sup>a</sup>       | Cut aitch bone                                |           |
|                         | <i>AiRA RBO Breast and Belly Opener</i> <sup>a</sup> | Open belly, breast, and throat                |           |
|                         | <i>AiRA RNC Neck Clipper</i> <sup>a</sup>            | Clip head (without removing the entire piece) |           |
|                         | <i>AiRA Splitters</i> <sup>a</sup>                   | Split the carcass longitudinally              |           |
| Lamb<br>Beef<br>Chicken | <i>Hamdas-RX</i> <sup>b</sup>                        | Debone back legs                              | [58]      |
|                         | <i>SRDViand project</i>                              | Debone back legs                              | [59]      |
|                         | <i>SCOTT Automated Boning Room</i> <sup>c</sup>      | Cut and debone certain parts                  | [57]      |
|                         | <i>SRDViand project</i>                              | Cut half carcasses                            | [59]      |
|                         | <i>GRIBBOT</i>                                       | Fillet breasts                                | [60]      |

<sup>a</sup> [www.frontmatec.com/en/pork-solutions/clean-line-chill-room/aira-robots](http://www.frontmatec.com/en/pork-solutions/clean-line-chill-room/aira-robots) (accessed on 23 June 2022); <sup>b</sup> [www.mayekawa.ca/mayekawaproduct/food/robotics/hamdas-rx/](http://www.mayekawa.ca/mayekawaproduct/food/robotics/hamdas-rx/) (accessed on 23 June 2022); <sup>c</sup> [www.scottautomation.com/products/automated-boning-room](http://www.scottautomation.com/products/automated-boning-room) (accessed on 23 June 2022).

Other similar robotic technologies are also available for lamb and beef carcasses. Thus, in the case of lambs, we find the *SCOTT Automated Boning Room*, which is an intelligent system that uses 3D scanners and X-rays to predict the best cutting route and achieve the deboning of certain parts of the lamb, such as the back legs [57]. On the other hand, for beef carcasses, there is the *SRDViand project* technology that allows to operate half carcasses. Specifically, the *SRDViand project* has a vision system (currently operational) capable of extracting information to count the ribs and identify the dorsal spine and a robotic arm that makes the appropriate Z-cut [59,61]. The vision system (namely “eye-to-hand”) consists of a camera and a projector that performs a 3D reconstruction by triangulation, through which the ribs and the dorsal spine are counted and identified, respectively. Thus, the cutting route is defined, and the hindquarters and forequarters are obtained. The path and conditions followed for the cut (forward speed, blade movement, blade lateral support on the bone, and blade angle) are readjusted from a theoretical path according to the characteristics found in situ (flank thickness, fat quantity, textural variability, etc.).

As for poultry meat, presently the industries that process these products are the most automated in the meat sector, since poultry have fewer variations between carcasses compared to other larger animals. However, automation processes take place in the first processing of poultry [62]. This fact, together with the high consumption of poultry meat, means that the industry continues to constantly demand intelligent systems that permit to increase the industry yield [57], especially in the second processing of poultry (cutting and boning) [62]. In this context, some successful systems have been developed, such as *GRIBBOT*, which is a chicken fillet-harvesting robot equipped with 3D vision, a personalized designed gripper, and a carrier system to expose the breasts to the robotic arm [60]. In this way, the *GRIBBOT* combines a 3D vision algorithm that allows calculating and locating the grip point on the breast for a suitable and fast (less than 4.75 s for a single fillet) extraction of the fillets.

Despite the great advances in robotization and automation, on many occasions these IR 4.0 technologies cannot be fully implemented in the meat industries due to biological variations of the raw material, the specific needs of washing and disinfection of surfaces, and/or economic viability on account of the high cost required for these technological processes. Nevertheless, the current trend rejects continuing to implement systems based on hard work performed by operators with the aim of providing a higher quality of work and reducing pathologies associated with it (musculoskeletal disorders). For this reason, technologies that combine human–robot collaboration are being investigated, creating the so-called CoBots, which would represent a very useful tool in the meat industry [32]. In addition, the use of CoBots would facilitate the inclusion of newly arrived operators since it would permit them to obtain a step-by-step approach to processing, achieving their training. In this field, the use of augmented virtual reality could improve the necessary skills that would otherwise only be acquired with years of experience [63]. An example of

the use of augmented reality can be found in the work carried out by Bologna et al. [63]. They investigated the training of operators without the cost of the material and avoiding possible risks for both equipment and personnel in real life, using Meta 2 glasses and the Unity 3D and Visual Studio software. The platform employed incorporated a graphical interface which included figures and terminology that provided the simulation of industrial equipment. This could reduce the lack of trained labour that presently exists in the meat sector.

On the other hand, IR 4.0 technologies must guarantee monitoring and be able to perform measurements in real time throughout the food supply chain. To carry out this monitoring in the meat industry, intelligent sensors must be used, which allow the monitoring and recording of the production line in real time. The sensors employed will depend on the parameters that are monitored on the production chain. The most widely utilised in food Industry 4.0 (and therefore the most applicable to the meat sector) are the optical sensors based on spectroscopy, which can afford a real fingerprint of meat products. In this way, the implementation of sensors in the food Industry 4.0 throughout the entire process permits the meat factory to include rapid, real-time, and continuous control of parameters as important as composition, nutritional quality, safety, and traceability of meat and meat products (topics that will be covered in the next section) [24]. Likewise, the sensors could allow the control of meat characteristics related to the production and the sustainability of its processing since; for example, when a meat defect is identified in real time in the production chain, action could be taken to obtain the appropriate product, that otherwise could reach the supermarket shelves and be rejected by the consumer (favoring food waste). Thus, the sensors, connected to various algorithms, are used to quickly capture and process a multitude of data that permit the creation of summaries and action plans (e.g., removing food that does not reach the required quality, return a product to a previous phase, etc.). Thus, due to their usefulness, these devices have evolved, giving rise to miniaturized and portable devices that are easy to implement in the meat industry [64].

In the case of the preservation of meat products, the use of smart sensors that can be incorporated into smart packaging materials in the form of films, labels, or barcodes with the aim of providing information on modifications in time and temperature, pH, humidity, gas levels, chemical composition, microbial contamination, etc., can be highlighted [65]. An example of these sensors applied to meat can be found as part of films in smart packaging. These films are generally made from natural polymers such as proteins and carbohydrates, which integrate the sensor itself into their matrix (generally also from a natural material, namely anthocyanins, curcumin, etc.). Thus, this smart technology has allowed monitoring the freshness of meats such as chicken [66–68], pork [69,70], beef [71,72] and lamb [73,74]. In this way, the sensors could help enhance the preservation of meat by being able to detect even minimal or subtle changes during its storage. However, it should be borne in mind that the natural materials used in smart packaging are still in the process of development and must be studied to obtain suitable packaging/sensors (structure, colour, resistance, etc.).

Parallel to sensors, IoT and blockchain technologies become essential tools to control the monitored results with the advantage of being technologies that help maintain the transparency of the results [75,76].

#### 4. Industry 4.0 Technologies Applied for Meat Quality, Safety, and Authenticity

Currently, consumers are not only centred on the sensory attributes of food products, but are increasingly demanding more nutritious, functional, minimally processed, low-additive, safer, and more sustainable foods. Besides, consumers are becoming more aware of the authenticity of nourishment and possible falsifications and counterfeits [77]. In this context, the meat industry is highly affected, since meat is the main source of protein of animal origin consumed by humans [78]. To satisfy these concerns, IR 4.0 has promising potential to increment and favour the reliability, quality, safety, and authenticity of meat and meat derivatives.

#### 4.1. Application of Industry 4.0 Technologies for Meat Quality

High quality is a key factor in today's hypercompetitive market [55]. Hence, predicting quality attributes including chemical composition, physicochemical parameters (pH, colour, water holding capacity, and texture) and sensory attributes of a meat product in the processing line quickly and non-destructively is a major challenge [79].

From this perspective, IR 4.0 technologies can be particularly beneficial in ensuring food quality, since methods using image techniques have been studied for the determination of different quality parameters (e.g., colour, texture and texture-related features, flavour, and freshness) with good results in different meat matrices [80–84].

Specifically in meat, the use of hyperspectral images has been extensively investigated for the prediction of many parameters related to its quality (Table 2). This imaging technology encompasses a computer with appropriate software, a spectrograph, a camera, and an illumination unit [85]. Thus, spatial and spectral information of the meat is obtained simultaneously, which forms three-dimensional (3D) data cubes that allow objects to be detected, identified, and quantified in more detailed images (two-dimensional (2D) data matrix). After a previous pre-treatment of these acquired data to reduce noise and redundant information and the selection of the image region of interest (ROI), the information is processed with multivariate analysis (principal component analysis (PCA), partial least squares regression (PLSR), stepwise regression, correlation co-efficient, artificial neural network (ANN), successive projection algorithm, etc.) with the purpose of original data modelling for classification or regression [80,86].

One example of this advancement was the work carried out by Cucha et al. [81], in which they successfully developed a technology based on hyperspectral imaging to determine the quality of pork fat (in terms of fatty acid content). Concretely, these authors related textural information with intramuscular fat content obtained through the traditional gas chromatography (GC) technique. Thus, using a PLSR algorithm, they concluded that texture features from hyperspectral images could be used to rapidly predict intramuscular fat without the need for tedious traditional techniques. Similarly, Craige et al. [82] successfully employed hyperspectral imaging to predict intramuscular fat content and fatty acid composition of lamb meat. Additionally, methods for detecting marbling (which is related to sensory quality) through hyperspectral images in beef have also been developed [87,88].

**Table 2.** Application of hyperspectral imaging for meat quality prediction.

| Meat/Meat Product | Predetermined Quality Parameters             | Reference |
|-------------------|----------------------------------------------|-----------|
| Beef              | Marbling level                               | [87,88]   |
|                   | Colour (L*, a*, b*), texture (shear force)   | [89]      |
|                   | Colour, pH, texture (tenderness)             | [90]      |
| Microwaved beef   | Colour (L*, a*), moisture                    | [83]      |
| Chicken           | Colour (L*, a*, b*), pH                      | [84]      |
|                   | Texture (springiness)                        | [91]      |
|                   | TBARS                                        | [92]      |
| Lamb              | Fatty acid content, chemical composition, pH | [82]      |
| Pork              | Colour, texture (GLCM), drip loss            | [93]      |
|                   | Intramuscular fat (fatty acid composition)   | [81]      |
|                   | Colour (L*), pH, drip loss                   | [94]      |
|                   | Texture (tenderness)                         | [95]      |
| Pork sausages     | TVB-N                                        | [96,97]   |
|                   | Colour (L*, a*, b*)                          | [98,99]   |

L\*: Lightness; a\*: Redness; b\*: Yellowness; TBARS: Thiobarbituric acid-reactive substances; GLCM: Gray level co-occurrence matrix; TVB-N: Total volatile basic nitrogen.

Hyperspectral imaging has also been used to predict the colour of various meat products during their processing because porphyrins of some pigments can absorb energy at particular wavebands during electromagnetic radiation [83,89]. An example is pork sausages, where this IR 4.0 technology has been used to predict the colouration associated with the employ of different casings [98,99]. Similarly, hyperspectral images have been utilised to determine the influence of microwave treatment on beef colour parameters, allowing monitoring of the changes linked with heating [83]. For this, a typical pushbroom hyperspectral imaging system (308–1105 nm) was employed and spectral information was

extracted from each image obtained in the range of 400–1000 nm (after an adequate calibration of the camera). Thus, quantitative prediction models (Savitzky–Golay-regression coefficients-multiple linear regressions (SG-RC-MLR) model) were established which allowed eight optimal wavelengths to be related to the values of  $a^*$ , permitting visualization of dynamic colour changes during heating through distribution maps [83]. Similarly, other studies have focused on the prediction of colour in fresh pork [94], beef [89], lamb [93], and chicken [84] meat with the aim of characterizing this important quality attribute.

Texture has also been another quality attribute widely monitored by imaging technologies [100]. In this way, hyperspectral imaging techniques are currently being utilised to predict meat structure and its texture attributes (juiciness, tenderness, hardness, gumminess, springiness, chewiness, etc.) in different types of meat such as chicken [91], beef [89,90], lamb [93], and pork [95]. For example, in chicken, Xiong et al. [91] employed a hyperspectral imaging system (400–1000 nm) and a PLSR and ANN for textural model calibration. Subsequently, they selected 10 optimal wavelengths through the successful projections algorithm (SPA) and established optimized SPA-PLSR and SPA-ANN models. Since SPA-PLSR showed better results, Xiong et al. [91] developed an image processing algorithm that allowed obtaining maps for chicken meat that permitted visualizing springiness parameter. Similarly in beef, hyperspectral imaging technology was also employed. Thus, ElMasry et al. [90] developed an image processing algorithm to visualize the texture after the selection of 15 different wavelengths through PLSR (starting from the initial region 900–1700 nm). For their part, Wu et al. [89] utilised a hyperspectral imaging system (400–1100 nm) to capture hyperspectral scattering images of beef steak. Thus, they established a multilinear regression (MLR) model to predict meat tenderness after selecting the appropriate wavelengths through stepwise regression.

Moreover, hyperspectral imaging has been used to evaluate other parameters related to the texture, such as the water holding capacity, drip loss, and the level of marbling already mentioned previously [87,88,93,94]. Even other parameters related to meat quality such as pH and the chemical composition (moisture, protein, and fat) have been predicted in various meat matrices [82–84,93,94] due to the characteristic absorption bands possessed by the functional groups of the meat constituents (C–H, N–H, O–H, and S–H). Thus, spectral imaging systems (400–1700) permit meat properties to be evaluated, mainly using linear regression algorithms (PLSR and MLR) [80].

In addition to the above attributes, imaging techniques can be applied to predict freshness indices of meat. In this way, methodologies that use hyperspectral imaging have been developed in order to foretell the content of certain substances related to meat spoilage, such as the total volatile basic nitrogen (TVB-N) and the thiobarbituric acid-reactive substances (TBARS), which are related to the degradation of proteins and the oxidation of lipids, respectively. Specifically, these prediction tools have been used in determining the freshness of pork [96,97] and chicken [92]. Specifically, in cured pork meat, Yang et al. [97] developed simplified models for monitoring TVB-N based on a system of hyperspectral images in the spectral range of 400–1000 nm. For this, they initially elaborated calibration models using PLSR and least-squares support vector machines (LS-SVM), which were later simplified with the selection of 9 wavelengths (using the regression coefficient for it). Subsequently, Yang et al. [97] evidenced the suitability of the MLR model, which allowed the mapping of TVB-N content in cured pork slices. For their part, Li et al. [96] predicted the TVB-N using a hyperspectral imaging and colorimetric sensors array system for data acquisition and processing with the utilization of an efficient back-propagation adaptive boosting (BP-AdaBoost) algorithm for data fusion and modelling. Xiong et al. [92] used a hyperspectral imaging system and selected 10 optimal wavelengths through SPA (located in the 400–1000 nm spectral range), to establish a simplified SPA-PLSR model for chicken freshness prediction. Finally, these authors developed an image algorithm for displaying TBARS values on distribution maps.

On the other hand, as can be deduced from hyperspectral imaging technology, the acquisition and possession of previous data plays a fundamental role in the elaboration

of predictive models that are robust. That is why BD could provide advances in meat quality, since the creation of meaningful data resources is essential for the derivation of solid predictive models and rigorous validation tests that help predict different parameters of meat quality [101].

Moreover, other IR 4.0 technologies are being used in the search for new solutions and innovations for meat quality inspection. Thus, Almqvist et al. [102] investigated the remote post mortem veterinary inspection of pigs using AR. Concretely, the authors used a remote two-way video communication where they only needed a non-veterinary technician who carried a smartphone and a wireless headset that allowed communication between the veterinarian and the technician. The remote control tests were carried out at a large-scale pig slaughter plant where standard on-site inspections were also carried out for later comparison. Thus, it was observed that the remote inspection using AR showed a high level of agreement with respect to the standard inspection (located between 75% and 92% for vague findings and subjective decisions and clear, easily distinguished findings, respectively). Additionally, these findings may represent a way to reduce the inspection costs in small slaughterhouses established in remote places without reducing the quality of the carcasses produced, since it avoids the displacement of veterinarians.

#### 4.2. Application of Industry 4.0 Technologies for Meat Safety

Food safety is one of the key areas of the food market and today it is being challenged by the global dimensions of supply chains [103]. At the same time, there is a growing concern about the health aspects of meat and its derivatives by consumers, who often have limited confidence in the safety of certain meat products [104]. For these reasons, the application of new IR 4.0 tools to control and guarantee the meat safety is fundamental in the development of the food industry, thus averting foodborne illness and outbreaks because of microbiological deterioration and contaminations [55]. Table 3 shows some of the applications of IR 4.0 technologies in the meat industry (or their potential use in this sector) aimed at improving food safety.

From the start of animal slaughter to obtaining the portion of meat or the final meat product that reaches the consumer, a multitude of tasks are carried out (skinning, plucking, eviscerating, boning, cutting, mixing, resting, stuffing, etc.). These operations expose the meat to environmental contamination and to contamination related to human handling since traditionally all processes were conducted by humans. In this field, robotization and automation allow meat and meat products to be obtained with less human contact, which greatly favours the reduction of the microbial load [59]. In addition, robotization and automation favour a higher processing speed [60], thus reducing the chances of contamination. In this way, microbiological risks are reduced with the implementation of robots and automation systems, increasing the safety of meat and meat products [29].

Although to a lesser extent than for meat quality estimation, hyperspectral imaging technology is also a potential tool in safety prediction as it can be used to determine contaminations and detect microbial growth [55]. Specifically, this methodology has been widely studied in poultry meat since it is an IR 4.0 tool that permits the elimination of faecal material contaminated carcasses [105], thus preventing the proliferation of bacteria such as *Salmonella*, *Campylobacter*, and *Escherichia coli*. Furthermore, in poultry products, microbial contaminations related to foodborne illnesses (such as *Enterobacteriaceae*, *Salmonella*, *Campylobacter*, *Escherichia coli*, and *Pseudomonas*) can be predicted with the use of hyperspectral imaging [106–111]. In the case of other meat matrices, hyperspectral images have also been employed in order to predict microbial contamination in real time. For example, Achata et al. [112] developed a prediction model (based on PLSR) to determine the total viable count (TVC) in beef, while Zhou et al. [113] proposed a model for *Pseudomonas fluorescens* prediction in pork (based on Baranyi model in combination with the Ratkowsky square-root model and the Huang model in combination with the Ratkowsky square-root model). In the case of TVC prediction, this is done mainly using wavelengths around 596 nm, which

are related to the oxyhaemoglobin absorption bands [114], meanwhile the differentiation of bacterial species is based on the different absorption spectra shown between them [115].

In the field of food safety, the topic of allergies also acquires special interest since around 8% of children and 5% of adults around the world have some type of clinically proven food allergy [116]. Considering the circumstances, the use of IR 4.0 technologies can favour the exhaustive control of a product in industries and/or provide valuable information that allows allergic people to be warned. In this field, there are different IR 4.0 technologies that permit allergens to be revealed, such as those created by Telspec Inc. (Toronto, ON, Canada), and Nima Lab (San Francisco, CA, USA) in 2014 and 2016, respectively. In the case of Telspec Inc., it has launched a scanner based on reflective near-infrared (NIR) spectroscopy which reveals allergenic substances in food by using a low-power laser that analyses the reflected light waves with the help of a unique cloud-based algorithm and a simple smartphone app [117]. For their part, the company Nima Lab created a portable sensor that allows the amount of gluten in a food to be simply quantified. Concretely, this portable sensor was developed by adapting antibody-based chemistry employed for allergen detection and consists of a scanner, a capsule where the foodstuff is introduced and an application where the results are displayed and collected [42].

**Table 3.** Application and possible applications of IR 4.0 technologies for meat safety.

| Meat/Meat Product    | IR 4.0 Technology               | Predetermined Safety Parameters/Security Improvement                      | Reference |
|----------------------|---------------------------------|---------------------------------------------------------------------------|-----------|
| Possible application | Robotization and automatization | Reduce human handling and processing time                                 | [29]      |
| Beef                 | HSI                             | TVC                                                                       | [112]     |
| Pork                 | HSI                             | <i>Pseudomonas fluorescens</i>                                            | [113]     |
| Chicken              | HSI                             | Fecal matter                                                              | [105]     |
|                      | HSI                             | TVC                                                                       | [108]     |
|                      | MSI                             | TVC, <i>Pseudomonas</i> spp.                                              | [107]     |
|                      | HSI                             | <i>Enterobacteriaceae</i>                                                 | [111]     |
|                      | HIS                             | <i>Enterobacteriaceae</i> and <i>Pseudomonas</i> spp.                     | [110]     |
|                      | HSI                             | <i>Pseudomonas</i> spp.                                                   | [109]     |
| Chicken products     | MSI                             | TVC, <i>Pseudomonas</i> spp.                                              | [107]     |
| Possible application | NIR                             | Allergens                                                                 | [117]     |
| Possible application | Portable sensor                 | Gluten                                                                    | [118]     |
| Sausages             | IoT                             | Monitoring of CCP, security assurance, and traceability during processing | [75]      |
| Possible application | IoT, BD, and RFID               | Improved traceability and consumer confidence                             | [76]      |

HSI: Hyperspectral imaging; TVC: Total viable count; MSI: Multispectral imaging; NIR: Reflective near-infrared; IoT: Internet of Things; CCP: Critical control points; BD: Big Data; RFID: Radio frequency identification.

Another important reason for issues related to food safety is the incomplete, opaque, and asymmetric information that reaches the consumer about certain food products. To solve these problems, it is essential to establish a reasonable and reliable traceability system that guarantees food safety, the integrity of information, and restores trust between consumers and the market, in addition to optimizing the structure data storage. In this area, systems based on IoT, blockchain, and BD provide ideas and methods to solve these problems that are so present in traditional traceability systems. Specifically, the application of IoT technology could efficiently control the appearance of incidents related to meat safety, since it permits incidents and sources of danger to be identified in real time and more precisely. This is possible because the IoT platform interacts with the existing smart physical objects in the production chain and allows the status and any information associated with said smart devices to be consulted, being able to act accordingly [75]. For its part, the use of BD helps to guarantee the authenticity of the data of the food companies [76].

#### 4.3. Application of Industry 4.0 Technologies for Meat Authenticity

Meat and meat derivatives have certain intrinsic (specie, breed, sex, etc.) and extrinsic (geographical origin, production system, food supplied, processing techniques,

etc.) characteristics that on many occasions are exploited for commercial purposes. For instance, certain breeds tend to present some qualities that are more appreciated by the consumer (see autochthonous breeds vs. commercial breeds). Identically, some farming systems (extensive vs. intensive), feeding (natural vs. commercial feed) or processing (traditional/artisanal vs. industrial) affect the perception and preference of consumers. Considering these circumstances, the ability to determine the authenticity of meat is a basic pillar to prevent food fraud, which continues to represent a health, ethical, religious, and economic danger to modern society [119]. Authentication can be defined as the facts to establish or confirm the authenticity of food, that is, the acts that lead to determining that the claims made about the meat are reliable [120]. In this context, IR 4.0 technologies in the meat industry are shown as a valuable tool to detect and reduce different types of food fraud (Table 4).

Regarding fraud related to breed, origin, breeding systems, feeding, and processing techniques, these can be avoided using technologies such as IoT and blockchain, since both allow exhaustive monitoring of traceability during the entire food chain [24,121]. Furthermore, IoT allows the implementation of various useful sensors (such as temperature, humidity, oil, salt, metal, colour, pH, and viscosity sensors) in determining food fraud through the Raspberry pi that controls the system sensors and the ZigBee module used to transfer the results [122]. Due to this, the increase of consumer confidence in the meat industry can be favoured since these technologies increment transparency [123].

Finally, one of the most common frauds in meat industry is the total or partial substitution of high-value meat by poor meat or offal or by including proteins from various origins to lower costs. On this matter, imaging technologies have been identified as successful tools to determine adulteration in minced beef [124–127], chicken [106,128], lamb [129], and pork [130]. In general, these technologies (i.e., hyperspectral imaging and laser induced breakdown spectroscopy) made it possible to develop prediction models to determine different percentages of adulteration in meat. To do this, different samples of pure and adulterated meat (in different concentrations) are used. The images obtained from the samples were acquired and calibrated (using different mathematical tools such as PLSR, regression coefficients, random forest, support vector machines, etc.) with the aim of obtaining simplified models capable of predicting meat adulteration [124,127,131].

**Table 4.** Applications and possible applications of IR 4.0 technologies for meat authenticity.

| Meat/Meat Product | IR 4.0 Technology | Main Advancements in Meat Authenticity                                                     | Reference |
|-------------------|-------------------|--------------------------------------------------------------------------------------------|-----------|
| Beef              | IoT               | Tracking of the animal (breed, origin, feeding, etc.) and of the processing of the product | [121]     |
|                   | Blockchain        | Ensure traceability and improve consumer confidence                                        | [123]     |
| Minced beef       | HSI               | Chicken meat detection                                                                     | [126]     |
|                   | MSI               | Horsemeat detection                                                                        | [124]     |
|                   | HSI               | Pork meat detection                                                                        | [125]     |
|                   | LIBS              | Offal detection                                                                            | [127]     |
| Minced chicken    | HSI               | Carrageenan detection                                                                      | [128]     |
| Minced lamb       | HSI               | Pork meat detection                                                                        | [129]     |
| Minced pork       | HSI               | Offal detection                                                                            | [130]     |
| Fat mixture       | RS                | Differentiation between beef tallow, pork lard, chicken fat, and duck oil                  | [132]     |

IoT: Internet of Things; HSI: Hyperspectral imaging; MSI: Multispectral imaging; LIBS: Laser induced breakdown spectroscopy; RS: Raman spectroscopy.

## 5. Future Perspectives and Conclusions

In the current era, the meat industry faces great challenges related to the efficient and sustainable production of food and the generation of quality and safe foodstuffs with proven authenticity. These challenges must be addressed optimally to meet consumer demand and improve their confidence in the meat sector. Against this background, this review demonstrated by examining the literature results that the appearance and implementation of 4.0 technologies (such as automation and robotization, Internet of things (IoT), Big Data

(BD), Augmented Reality (AR), blockchain, imaging technologies and smart sensors) in the meat industry are presented as effective tools in the reliability, quality, safety, and authenticity of meat and meat products, as they provide substantial innovative solutions, resulting in improved global health, climate, environment, and economy.

However, these new technologies are still under development to improve their implementation in the meat sector, since on many occasions such implantation can be difficult due to the intrinsic characteristics of the meat and meat products, and also due to the complexity of the technologies themselves (both hardware and software). Moreover, these technologies currently imply a high implementation cost, which can be difficult to assume by many companies in the meat sector. For this reason, research must continue both to improve the available technologies and to reduce the costs of their implementation.

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## **Meat 4.0: principles and applications of industry 4.0 technologies in the meat industry**

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