



THE POTENTIAL OF ARTIFICIAL INTELLIGENCE IN THE MEAT INDUSTRY

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Abstract

This review considers the potential of artificial intelligence (AI) technologies in meat science and the meat processing industry, including its application in livestock and poultry farming, meat production, sensory evaluation, and personalized nutrition. The review presents approaches to classification of AI technologies used in the food industry and provides their characteristics, description of their constituent components, technical concepts and practical applications. AI is an important tool of support in the food industry and animal husbandry. The review thoroughly examines the application of AI in processing plants: 1) for quality control and sorting (computer vision); 2) for food safety improving (machine learning); 3) for optimizing the production lines (forecasting analytics), as well as in animal husbandry: 1) real-time health monitoring; 2) supervision over the animals' living conditions; 3) feeding optimization. In addition, the review pays special attention to AI using for authentication, identification, classification, and forecasting of the meat products. The development of technologies and the expansion of AI application scenarios in the meat industry will keep expanding. However, despite the significant benefits of AI applications, the article highlights several issues, challenges and limitations that AI encounters, such as privacy and security issues, technical complexity, and integration with the traditional methods of food processing. Nevertheless, technology of artificial intelligence possesses great potential in livestock farming and meat processing for increasing productivity, ensuring product quality and safety, and streamlining management. AI's potential will enable more efficient, safe, and sustainable development to provide consumers with high-quality food products.

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Introduction

Nutrition science is a field of knowledge that encompasses multiple scientific fields, including chemistry, physics, biochemistry, microbiology, technology, and food engineering, among others fields, it also offers potential for interdisciplinary research in agriculture, pharmaceuticals, medicine, and economics. In recent decades, a complementary combination of research in food science and technology, as well as the food industry with artificial intelligence, has been rapidly developing. Artificial intelligence plays a significant role in the modern food processing cycle, from the primary processing of agricultural raw materials to the analysis of quality and safety indicators of food raw materials, products, and packaging [1].

Artificial intelligence (AI) is nowadays permeating every aspect of our lives, and meat production is no exception. AI is revolutionizing the food industry by optimizing technological processes, improving food quality and safety, encouraging introducing of innovation into food production [2,3]. In terms of rapid growth of global food consumption, the use of AI algorithms in food processing

from farm to mouth promises to ensure both sustainable production and greater efficiency.

AI has become a transformative force in many industries, with its efficiency particularly noticeable in the food industry [4–6]. The study [4] reviewed the ability of AI to address the negative impacts of population aging on economic growth and industrial structure. The rapid development of AI offers new solutions to cope with labor shortages caused by population aging. Using data from 30 provinces in China, the authors analyzed the influence of population aging on food security and the role of AI, thus coming to conclusion that the application of AI is beneficial for food security.

The studies [5,6] summarize the most up-to-date technologies of Food Industry 4.0 and discuss the understanding of new trends in the food sector that have appeared as a result of the technological revolution. It is noted that technologies of Industry 4.0 have significantly changed the food industry and led to significant consequences for the environment, economy, and human health. Despite the importance of each and every of the above-mentioned

technologies, the true revolutionary sustainable solutions can only emerge through the simultaneous integration of many technologies. The era of Food Industry 4.0 features new challenges, opportunities, and trends that have changed current strategies and prospects for food production and consumption models, thus having paved the way to the Industry 5.0.

The historical development of AI in the food industry is shown in the Figure 1.

Initially focused on automating simple tasks, artificial intelligence has evolved into the advanced machine learning, forecasting analytics tool and integrated systems for real-time decision-making. Integrating AI technologies into food production, safety, supply chain management, and quality control can significantly improve efficiency, accuracy, and sustainability. As the global food industry faces increasing pressure caused by population growth, resource deficit and demand for higher food safety and quality standards, the implementation of AI-based solutions offers promising opportunities to cope with these challenges [7].

According to the analytical report of the Federal Center for Applied Development of Artificial Intelligence that functions under aegis of the Ministry of Industry and Trade of the Russian Federation [8], the experience of implementing AI solutions as of 2024 distributes in the following way: 35 % of enterprises have experience using AI solutions; 40 % do not use AI solutions; 25 % are at different stages of implementation. The Center's analysts note that the main advantages of implementing AI solutions are related to: automation and optimization of processes (20 %); improved quality of the products and services (18 %); in-

creased efficiency and productivity (17 %); expenses lowering and cost reduction (13 %); improved decision-making process (10 %); reducing human factor influence (7 %); acceleration of business processes (7 %); control over the staff's tasks (4 %); reduction of injuries (4 %). Despite significant advantages, there are also disadvantages to the implementation of AI solutions. This is mainly explained by the high costs of AI implementation and operation (23 %) and technical difficulties (18 %).

According to the definition of S. J. Russell and P. Norvig in the book *Artificial Intelligence: A Modern Approach* "The field of artificial intelligence, or AI, is concerned not only with understanding but also with creating intelligent objects — machines that can figure out how to *act effectively and safely in a wide variety of new situations*" [9].

Artificial intelligence includes: 1) machine learning, which focuses on developing algorithms that enable computers learning from data and make forecasts or decisions without explicit programming. By applying machine learning models, patterns in food safety can be established to detect risks of contamination and optimize storage conditions [10]; 2) deep learning, a subdivision of machine learning based on neural networks with many layers included; 3) natural language processing (NLP) deals with the interaction between computers and people through natural language. By analyzing customers' feedback on food safety, it helps producers (retailers, marketers) improve quality and solve safety problems [11]; 4) computer vision (or technical vision). The creation of machines that identify and classify objects visible in images and videos. With the use of computer vision, automated checking for

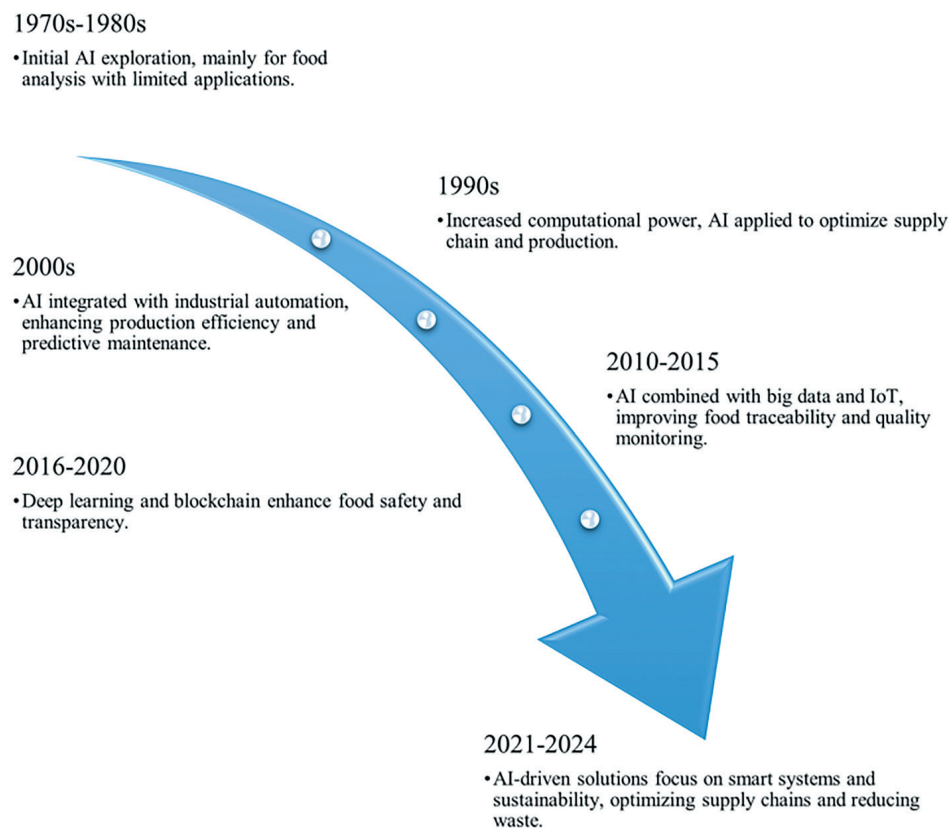


Figure 1. Historical development of AI in the food industry [7]

presence of contamination, checking food quality and labeling accuracy occurs, thus reducing the number of errors related to the human factor [12]; 5) robotics. Integrating AI into physical devices to perform tasks in the real world; 6) expert systems — programs that simulate solving of a problem that requires human expertise in a given field. They use knowledge bases and inference rules to make decisions; 7) agent-based systems — models where agents (software entities) can act autonomously, on their own, in an environment, making decisions based on their observations and goals.

The concept of AI is inseparably linked with the following technologies:

- 1) Big data is the vast quantity of structured and unstructured data required to train many AI models, especially to machine learning and deep learning. By analyzing big data, food companies can better understand market demands, optimize supply chains, reduce waste, and improve production efficiency. By combining big data technology with blockchain, it is possible to ensure traceability of the food products origin and quality, ensure transparent tracking from field to table, and provide the consumers with reliable, versatile information on the product [13,14];
- 2) Cloud computing provide the computing power and infrastructure required to train, test, launch and run complex AI models;
- 3) The Internet of Things (IoT) — sensors and devices that generate data that is analyzed by AI. They enable real-time monitoring of temperature, humidity, and freshness to ensure food quality during its storage and transportation [15].

Artificial neural networks (ANN) are a well-known mathematical tool that has recently been widely used and now being tested to solve problems related to meat production and meat processing technologies. Their advantages include their capability to handle nonlinear data, highly correlated variables, and the potential for problem detection or classification. Specifically, promising applications of ANNs in the meat sector include carcasses classification, quality control and safety control of raw materials and finished products, meat processing, spoilage prevention, ensuring freshness and shelf life assessment, off-flavor detection, authenticity assessment, and many more other functions.

Artificial intelligence and machine learning technologies have now moved from the experimental development stage to integral components for optimizing agricultural processing and food production. Initially, AI technologies were developed to analyze complex data sets, predict consumer behavior, and improve production efficiency. The integration of AI and machine learning in the food industry continues to expand, offering significant opportunities to address quality assessment and control issues, improve food safety, and enable future innovation. However, it is important to consider the potential drawbacks of excessive

reliance on AI and machine learning in food production, such as the risk of human jobs losses and the possibility of errors or biases in algorithmic decision-making process. Furthermore, the cost of implementing and maintaining AI technologies may be prohibitive for some small-scale producers of food [16].

With the constant advancement of technology and the expansion of its application scripts, the prospects for AI application in the food industry will keep expanding. It is becoming an important tool for digital transformation and modernization of the food industry, thereby enhancing its competitiveness.

Effective use of AI requires solving of long-term issues, including data protection, complex integration, ethical questions, and staff development. Artificial intelligence offers the potential for supply chain integration, production of personalized nutrition, and implementation of sustainability initiatives, even with initial capital expenses. To scale AI for food industry optimization in the future, balancing ethical obligations with technological advances, effective collaboration of various concerned parties is crucial.

A summary of the literature references shows that the primary goal of AI is to develop systems capable of understanding natural language, identifying patterns, and autonomously adapting to new knowledge. While significant progress has been achieved, ongoing research consistently refines algorithms and strategies to widen the capabilities of artificial intelligence in any fields [16].

The purpose of this review is to systematize the various applications of artificial intelligence in the food industry, with a primary focus on the meat industry, highlighting the potential of artificial intelligence in the field of cattle carcasses classification, automation of various technological operations in meat production, detection of food adulteration, ensuring traceability and determination of meat quality and safety with higher accuracy, the use of machine learning in cultured meat technology, and other areas, while simultaneously encouraging the formation of technological innovations and sustainable development of the meat industry.

Objects and methods

The bibliographic analysis included two stages: (1) collecting research publications relevant to the topic and to the purpose of the study; and (2) detailed review and analysis of the scientific information presented in these publications.

In the first stage, from April to November 2025, a keyword-based search was run for the articles published in English and Russian between 2011 and 2025. The scientific databases Scopus, IEEE Xplore, and ScienceDirect were the sources, as well as the scientific indexing web services RINTS and Google Scholar. These databases were selected to provide a sufficiently large initial tray of samples of the relevant articles. The publication selection process began with an assessment of the titles and abstracts content.

Duplicate references obtained from different databases were ignored. The following keywords were used in the search query: “artificial intelligence”, “convolutional neural networks”, “machine learning”, “deep learning”, “computer vision and image processing”, “livestock and poultry farming”, “meat production”, and “food quality and safety.” The general term “food safety” was included into the search strings, despite the fact that the study focused on the use of AI technologies in livestock farming and meat production. This was caused by the difficulty of clear definition of the search strings related to these specific aspects of meat technology without excluding too many relevant articles. Using more general terms allowed us obtaining a larger set of references, which in the next step were screened for relevance to the research topic.

Thus, the studies referencing to the use of AI technologies but not related to the food industry, specifically meat processing, were filtered off. This activity initially found 417 articles. By limiting the search to the appropriate application of AI technologies in the food industry, with specific reference to the meat industry, and substantive conclusions, the initial number of articles was reduced down to 142.

To ensure a thorough and transparent review of the existing literature on the application of AI in food systems, a systematic approach was adopted, based on clearly defined criteria of inclusion and exclusion. These criteria ensured that only high-quality and relevant studies were considered.

The following inclusion criteria were used to confirm the required application:

1. Using AI-based methods and/or approaches as a method for solving the problem under study.
2. Solution of the problem and/or task most related to the agro-industrial complex the following areas: the use of artificial intelligence in livestock and poultry farming, meat product tracking, authentication and detection of meat product adulteration, meat product production, including cultured meat, assessment of its quality and safety, establishment and control of expiration dates and packaging of food products.
3. The studies considered applied artificial intelligence technologies such as machine and deep learning, computer vision, convolutional neural network, artificial neural networks, random forest (RF) method [17] to optimize food systems.
4. Systematization of practical results using some clearly defined performance indicators that indicate the success (efficiency) of the AI method used in the agro-industrial complex.

Exclusion criteria:

- Studies that lack a clear methodology or sufficient data to replicate the results.
- Articles not published in peer-reviewed journals or that exhibit a high degree of bias, thereby compromising the validity of their findings.

In the second stage, the 142 papers selected in the first stage were sequentially analyzed, taking into account the following research questions: (a) the problem they reviewed, (b) the approach used, (c) the data sources used, and (d) general accuracy. Information was also systematized according to the following areas: (e) whether the authors compared their AI-based approach with other methods, and (e) whether the efficiency of the developed method was assessed in comparison with others. It is also taken into account that the use of various artificial intelligence technologies (methods) in the food industry allows for the implementation of specific tasks of a specific research area to ensure its maximum effectiveness.

Technologies of artificial intelligence using in the food industry

Classification of AI technologies used in the food industry

Currently, advanced technologies, artificial intelligence (AI), and especially machine learning (ML), are being actively implemented in various industries and services. Food science and technology and related issues are no exception. Improving agriculture, maximizing the utilization of agricultural raw materials, developing new food products and nutraceuticals, more accurate sensory evaluation, industrial processing, improving food quality, ensuring food safety, supply chain management, waste recycling, and, finally, calorie and nutrient assessment are some of the achievements of the combination of food science and artificial intelligence (AI) [1].

To assess the potential of AI in food industry technologies, AI was classified taking into account the main approaches, methods and components (Figure 2).

I. by capabilities level:

1. specialized (narrow) AI (Artificial Narrow Intelligence, ANI, or Weak AI). The specialized AI is designed to solve one specific problem or some narrow range of problems. It currently dominates. Examples of specialized AI use cases include facial recognition, voice assistants, recommender systems, chess/Go game, spam filters, autopilots. This type of AI does not possess general consciousness, self-awareness, or the ability to apply knowledge outside its specialization;
2. general AI (Artificial General Intelligence, AGI or Strong AI). It is hypothetical AI that features intellectual abilities comparable to those of humans. It is capable to understand, learn, and apply knowledge to any intellectual task;
3. superintelligence (Artificial Superintelligence (ASI). A hypothetical AI that significantly exceeds the intellectual abilities of the best human minds in virtually all areas, including scientific creativity, general wisdom, and social skills.

II. by functionality and approach:

1. Reactive Machines. Basic systems: they have no memory and do not use past experience; they respond only to current input data. An example is the IBM chess

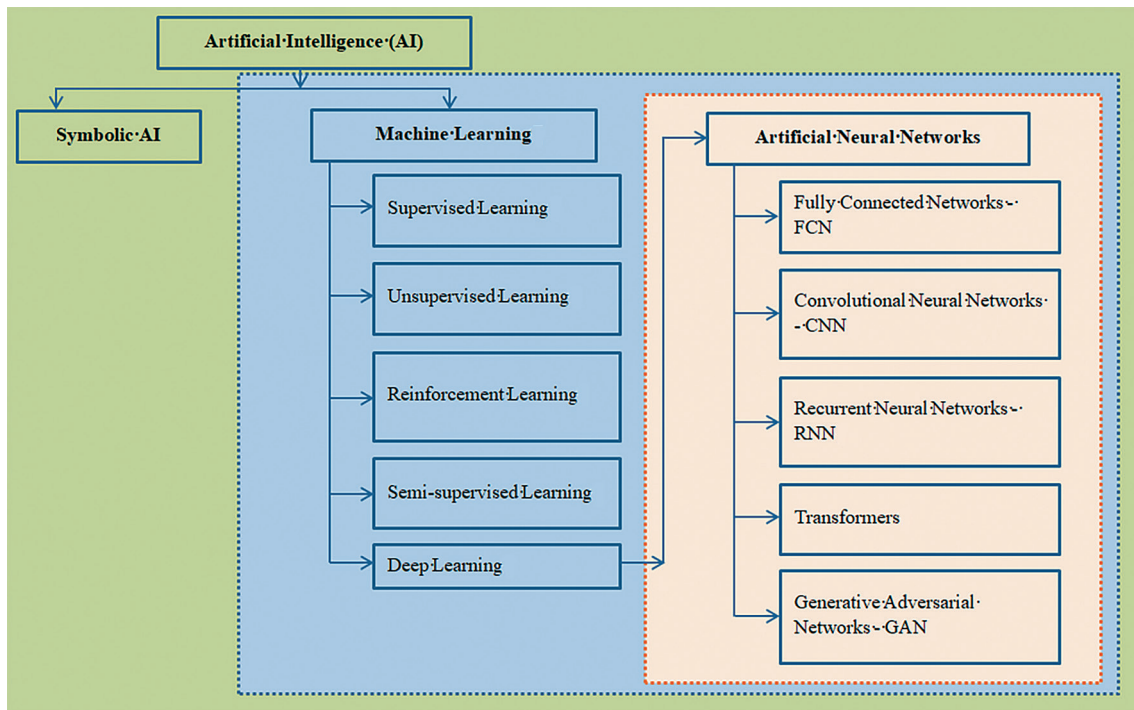


Figure 2. Artificial intelligence (AI) classification split into main approaches, methods, and components

computer — Deep Blue — who won over Kasparov. It analyzed the current position on the board;

2. Limited Memory systems use recent experience (data) to make decisions, it possesses short-term memory. Most modern systems are based on Machine Learning (ML), including self-driving cars (which are capable to analyze recent data obtained from sensors), chatbots (taking into account the context of the dialogue);
3. Theory of Mind. The hypothetical AI capable of understanding the emotions, intentions, beliefs, and thoughts of other beings (people, other AI), and which features forecasting behavior.
4. Self-Awareness. The hypothetical AI that is conscious, self-aware, understands its own state, and is able to forecast the feelings of others.

III. by techniques and methods (technical classification):

1. Symbolic AI or Rule-Based AI. In early approach — it uses written logical rules and symbolic (fact) manipulation to represent knowledge and make decisions. It is a component of expert systems, programming logic (Prolog), and simple decision trees.
2. Machine Learning (ML). A key component of modern AI. The algorithms are used that allow computers to learn from data without being explicitly programmed for each task. They identify patterns and build models for forecast or for making decisions. The following types of machine learning exist: a) Supervised Learning — the algorithm learns from labeled data (there are “correct answers”); b) Unsupervised Learning — an algorithm that searches for hidden structures (patterns) in unlabeled data; c) Reinforcement Learning (RL) — the algorithm (agent) learns by interacting with the environment, receiving “rewards” or “penalties” for ac-

tions; d) Semi-Supervised Learning is a combination of labeled and unlabeled data.

Machine learning includes algorithms such as linear regression, support vector machine (SVM), Random Forest, k-nearest neighbors (KNN), k-means, DBSCAN (Density-Based Spatial Clustering of Applications with Noise), etc.

3. Deep Learning (DL). A subset of ML that uses artificial neural networks (Artificial Neural Networks (ANNs) with many layers (“deep” networks) for learning data representations at increasingly higher levels of abstraction.

There are the following types of ANN: a) Fully Connected Networks (FCN). The basic type, each neuron in a layer is connected to all neurons in the next layer; b) Convolutional Neural Networks (CNNs) are optimized for processing grid data (images, videos). They use convolutions to detect the local patterns; c) Recurrent Neural Networks (RNNs) are designed for sequential data (text, speech, time series). They have a “memory” of previous inputs; d) Transformers. The modern architecture that dominates in Natural Language Processing (NLP) uses the attention mechanism to analyze the dependencies between all sequence elements, regardless of distance; e) Generative Adversarial Networks (GAN). Two networks (generator and discriminator) compete, which allows generating new, realistic data (images, music, text); f) Autoencoders. Networks for learning the efficient data representations (compression, noise reduction) or generation.

Evolutionary Algorithms. Optimization methods inspired by biological evolution (selection, mutation, crossbreeding). They are used to solve problems where traditional methods are ineffective.

5. Natural Language Processing (NLP) is a field of AI that deals with the interaction between computers and human language. It utilizes methods from machine learning (especially deep learning) and linguistics.
6. Computer Vision (CV). The field of AI that enables computers to “see” and understand visual information (images, videos) relies on CNNs and other deep learning methods.
7. Robotics. The application of AI to control physical robots. It combines CV, NLP, ML (especially RL), motion planning, and reactions to sensors’ signals (sensorics).
8. Expert Systems. An early successful form of AI that uses a knowledge base (rules and facts) and a logical inference engine to solve problems like a human expert in a narrow subject area. It is considered a symbolic AI.

One of the dynamically developing areas for the researchers, scientists and experts in recent decades has been the mutually complementary combination of researches in food science and technology, as well as food industry with artificial intelligence [1,18].

The following AI methods are most actively used in the food industry.

Machine learning

Artificial intelligence is a broad field that models human intelligence processes using machines and computers and develops systems to perform tasks that typically require human intelligence. Machine learning (ML) is a subset of artificial intelligence that enables machines to automatically learn from given data by implementing statistical algorithms and models [1]. Machine learning and automation have become widespread in the field of food safety and quality assurance. Automation combined with artificial intelligence is used for forecasting of crop yield, customers’ demands analysis, sorting, quality control of food samples, and many more tasks [19].

Machine learning is divided into four categories: supervised learning, unsupervised learning, reinforcement learning, and representative learning. Supervised learning: Forecast for unobserved points is performed using supervised learning [20,21]. Machine learning has demonstrated its effectiveness in forecasting sales and the amount of food waste generated [21]. Risk assessment of various natures is a decision-making tool in many fields, including the food industry. Developers are trying to incorporate genetic information into the modeling system using machine learning to reduce uncertainty in modeling food safety risks. This supervised learning technology enables forecasting the severity of diseases caused by pathogens such as *Salmonella* and *Listeria* based on genome sequencing data. The author was able to extrapolate clinical cases of foodborne *listeriosis* contamination using multilocus typing of the whole genome sequence [20]. In particular, machine learning is a powerful tool for assessment of food safety risk, assisting in the automatic recognition and classification of food defects, spoilage and shelf life forecast, risk pattern recognition, and rapid de-

tection of food ingredients and hazardous materials [22,23]. Due to the interdisciplinary nature of food-related research, machine learning for food covers various research areas, such as image recognition, ingredient analysis, supply chain optimization, and taste forecast [24].

In [25], a non-invasive and non-destructive automated quality control system based on computer vision and ensemble machine learning methods is proposed for the meat industry. The system determines all physicochemical, textural, and sensory quality characteristics of pork and beef tenderloin in four meat states (fresh, defrosted, cooked, and cured) with high accuracy (0.74 for pork loin, 0.76 for beef loin), thus representing a real alternative to the traditional methods for the food industry processes.

Deep learning

Deep learning is a branch of machine learning. It uses ANN (Artificial Neural A neural network (also known as a deep learning network) is designed to simulate the human brain and is built on a deep hierarchy of layers that solve complex problems. This enhances the capabilities of supervised and unsupervised learning algorithms to solve complex real-world problems by adding various processing methods [20]. Deep learning is used for determination of a range of food characteristics, such as determining the quality of fruits and vegetables, estimating calories content, and so on.

Sensory evaluation plays an important role in determining the quality of food products. Therefore, researchers are interested and willing to invest more effort in this area to forecast sensory characteristics and eating conditions using traditional data processing methods such as PLSR, SVM, and neural networks. Machine learning methods are used to establish the relationship between texture, sensory characteristics, and physicochemical parameters of food products [20]. Research on sensory characteristics is based on traditional data analysis methods, including extraction of features from images, statistical analysis, etc. Deep learning is rarely used for features analysis [26].

The study [27] presents a comparative analysis of the efficiency of various machine learning algorithms based on raw data obtained from the analysis of organoleptic, sensory and nutritional properties of meat, for differentiating categories of commercial lamb from the local Spanish breed (*Mallorquina breed*) obtained in the following production systems: milk-fed lambs; pasture-raised lambs; light breed lambs; and grain-fed pasture lambs. Six machine learning algorithms were evaluated: artificial neural network (ANN), decision tree, k-nearest neighbors (KNN), naive Bayes algorithms, multinomial logistic regression, and support vector machine (SVM). The results of this study demonstrated that machine learning is a useful tool for classifying commercial lamb carcasses. Accuracy in the assessment of the organoleptic and sensory datasets was 88 %, in the nutritional dataset it was 83 %, and in the combined datasets it reached 88 %.

In the study [28], the integrated systems for real-time food freshness measurement were developed to improve the reliability, safety, and sustainability of food supplies. The system combined a metal-organic mixed-matrix framework membrane with deep learning technology. Four state-of-the-art deep convolutional neural networks were used to recognize color changes, thus enabling highly accurate freshness assessment. In a simulation test for assessing chicken freshness, an accuracy of up to 98.95 % was achieved via using the WISeR-50 algorithm.

In the article [29] an open database of Chinese food images with nutrient data was represented. The database got the name ChinaFood-100, it contains 10,074 images systematized into 100 categories of popular Chinese dishes, including staples, meat, fish, and vegetable dishes. The database structure includes two main groups: staples and dishes. For each image of a single dish, detailed information on the content of 23 food nutrients is provided. The data is based on the official document “Dietary Guidelines for the Chinese Population”, which ensures compliance with national standards and the scientific validity of the annotation to the dish image. The ChinaFood-100 database is a structured, annotated, and scientifically valid resource designed to support research at the intersection of computer vision, dietetics, and food habit analysis, with an emphasis on Chinese cooking specifics. Based on this database, four state-of-the-art deep learning neural network architectures were studied. The results showed that Inception V3 achieved the highest image recognition accuracy, reaching 78.26 % and 96.62 % for top-1 and top-5 accuracy, respectively, while the lowest score was achieved using VGG. The results of ROC and mAP showed that the diversity of food images in each category significantly impacted the model’s performance. The authors suggested that increasing the image sample size in some categories with low recognition accuracy (e.g., braised pork leg (#66), fried minced celery (#87)) are able to improve image recognition accuracy in the future.

Computer vision and image processing

Computer vision systems (CVS) is an important branch of artificial intelligence that studies how computers receive, process, analyze, and understand digital images, videos, and other visual data to enable computers to mimic the human visual system.

Computer vision is the acquisition and processing of images. The past decade has witnessed a significant growth in machine vision-based researches in the food industry. Machine vision-based food image analysis has become an important research area aimed at solving complex problems in the food industry, providing broad development prospects for scientific research to solve food safety and quality issues, food system development, and food processing. Machine vision-based image recognition refers to the classification and recognition of images with the help of machine vision technology, in which various objects in

some image are distinguished into certain types and get category label to identify the object, function, or content in the image. The workflow of image recognition can be divided into the following steps: image receiving, image preprocessing, image segmentation, features extraction, image recognition classification, models training and optimization, and models testing and evaluation [30].

Machine vision (MV) is a technology that automatically extracts information from images via a computer. Machine vision, a synonym for computer vision, refers to the use of a device for contactless optical sensing and computational processing for automatically receiving and interpreting the image obtained. The goal of the technology is to match the functions of human vision through electronic perception and evaluation with the help of images. MV systems offer extensive capabilities for automating manual assessing, standardizing methods and eliminating the tedious task of data verification by human. These systems work by capturing an object image, like a piece of meat, processing the image to measure desired parameters, and comparing these parameters with predetermined inspection criteria, helping to make decisions about corrective actions for the object itself or production process. The most significant advantage of meat inspection with MV systems is its non-destructive nature when examining a meat sample. Recently, there has been significant growth of MV application in various fields, such as: poultry carcasses inspection, weight forecast, beef color determination, meat tenderness forecast, and chemical component forecast of meat and meat products. However, certain disadvantages of this method should be noted. MV technology requires uniform illumination and calibration. It is often challenging to separate overlapping objects from the background when it is necessary to assess both sides of a meat product [31].

The study [32] explored the feasibility of using computer vision technology to improve traceability and quality control in the red meat industry. Extensive experiments with beef steaks (602 pcs) demonstrated that internal meat characteristics can serve as reliable identifiers for traceability while simultaneously providing automated quality assessment. The developed quality forecast module, based on the EfficientNet model, achieves high accuracy in forecasting marbling scores (96.24 % top-1±1, 99.57 % top-1±2), breed identification (91.23 %), and cattle diet determination (90.90 %).

Consumers often struggle to assess the organoleptic qualities of meat, which are influenced by tenderness and intramuscular fat. In study [33], the computer vision system (CVS) was developed which uses smartphone images to determine the tenderness of beef and pork steaks (1), predicts shear force and intramuscular fat content (2), and runs a comparative analysis between consumers’ ratings and the results of the method (3). When classifying beef as tender, the model achieved an accuracy score (F1) of 68.1%. After changing the dataset category to “tender” and “tough”, the F1 score for tenderness increased to 76.6%.

For pork loin tenderness, the model achieved an F1 score of 81.4%. This score improved slightly to 81.5% after splitting into two classes.

Fuzzy Logic Technique (FLT)

FLT is widely used in industry due to its ease of use and rapid and accurate problem-solving capabilities. By controlling human thinking in linguistic terms, FLT is used in the food business to model, control, and classify food products, as well as to solve food-related problems [34]. FLT can analyze factors like temperature fluctuations during transportation, humidity level, and ethylene level to forecast the remaining shelf life of fruits and vegetables more accurately than traditional methods. FLT can be used for sensory evaluation of bread or cakes to assess texture, taste, and appearance, integrating subjective feedback from panels into quantitative data for product development. Fuzzy analysis of the organoleptic properties of food products at various stages of machine operation can be used to optimize processing steps based on desired product characteristics [2]. Fuzzy modeling can be used to optimize process parameters like soaking time, cooking time, frying temperature, and raw material properties (particularly — the slice thickness) in the production of taro chips [35].

AI technologies in livestock and poultry farming

Careful management of farm cattle rearing has become an important means of improving production efficiency in the livestock industry. Monitoring and recognizing livestock behavior are of great importance for the development of precise farming of livestock. For example, individual animal behavior is related to the amount of water and feed consumed and is important for improving animal productivity. The social behavior of animals can provide important information about their well-being; for example, aggression between pigs can cause skin lesions, infections, and even lead to fatal injuries. Feeding behavior, as one of the behaviors of sows during lactation, is crucial for the early survival and growth of their piglets before weaning, which has a significant impact on the economic benefits of pig farms. Furthermore, the movement of animal body parts can be used to detect diseases; for example, clinical lameness provides a significant impact on milk yield and reproductive function. Assessing animal's posture is a key step in analyzing its behavior and assessing health, and therefore is of great importance for rational livestock breeding [36].

However, despite the growing demand for smart farm management solutions, the implementation of advanced technologies like artificial intelligence and big data to improve livestock productivity is relatively slow compared to other sectors such as healthcare, infectious diseases surveillance, and production. The importance of such AI-related research and development is underestimated, and additional efforts are required. The combination of artificial intelligence with the end-to-end Internet of Things (IoT),

fog computing, and cloud computing will undoubtedly accelerate the development of smart farm management [37].

Traditional manual observation of pig and cattle behavior is labor-intensive, human subjective, and difficult to achieve in continuous and large-scale operations. It is not surprising that computer vision technology, with its advantages of objectivity, non-invasiveness, and continuous operation, has been widely explored for its use in livestock behavior recognition in recent years. However, computer vision technology faces certain challenges in livestock behavior recognition research, such as complex animal interaction scenes, variable lighting, occlusion, touch, and overlap between livestock, thus limiting the rapid transfer of the technology to industry [36,38].

Image segmentation and identification are the foundation of livestock behavior recognition. Therefore, the development of reliable algorithms for livestock identification, behavior recognition at different growth stages, and subsequent quantitative evaluation of behavior recognition results are the foundation for constructing a system for assessing the growth, health, and well-being of animals. The role of image segmentation is to extract target foreground objects from the background, and the effect of image segmentation directly affects the accuracy of features extraction and behavior recognition among the livestock [39]. The role of identification is to determine the identity of each individual in a group, and this identity can localize the recognizable behavior down to a specific animal, thereby implementing the transition from group behavior recognition to recognition of the individual behavior [40].

Accurate forecast of cattle body weight is critical for herd monitoring, assessing biological efficiency, and optimizing feed management. Researchers evaluated a cattle body weight forecast model using morphological data from 465 lactating cows of Holstein breed, including dorsum length (DL), thoracic width (TW), abdominal width (AW), rump width (RW), hip height (HH), body depth (BD), thoracic perimeter (TP), and abdominal perimeter (AP). Spearman's correlation analysis identified the measurements TP ($r = 0.89$), AP ($r = 0.88$), and RW ($r = 0.80$) as the strongest predictors. Simple and multiple linear regression models, artificial neural networks (ANN), and support vector regression (SVR) were tested to forecast dairy cattle body weight. The dataset was divided into 90% for training (419 samples), 5% for validation (23 samples), and 5% for testing (23 samples). The results achieved in this study demonstrated that the use of morphological measurements, even manually collected, allows for the creation of highly accurate forecasting models for estimating cattle body weight based on machine learning methods. In the best simple model using only the TP indicator, R^2 (the coefficient of determination) was 0.7763, and RMSE (root mean square error) was 43.69 kg. The multiple regression model with TP, AP, and RW improved the performance ($R^2 = 0.9067$, RMSE = 28.00 kg). As a result of the evaluation of the obtained results, it was

noted that although regression models are quite effective, the use of artificial neural network (ANN) ($R^2 = 0.9125$, RMSE = 25.86 kg) and support vector regression (SVR) ($R^2 = 0.9046$, RMSE = 27.41 kg) ensures greater accuracy, which enhances their potential for herd management. However, simpler models still remain viable alternatives for their practical application in farms [41].

Measuring animals with a tape measure to determine their weight is quite labor-intensive and causes animals' stress, which leads to weight loss and productivity of 5–10%. Therefore, computer vision technologies are increasingly being used to assess the live weight of cattle through contactless morphometric measurements, which eliminates the need for linear measurements or weighing cattle on scales. In developing an effective model for forecasting the live weight of cattle, methods were proposed for preprocessing RGB images and a depth map (side view of the animal) and creating a color RGB projection and 2.5D depth map for forecasting live weight based on image regression using deep learning methods. Contactless measurement of live weight of cattle can be used: for an objective assessment of breeding animals during grading; livestock valuation; justification of the further use of young animals, and the development of a technology for assessing the health and productivity of animals in industrial fattening complexes [42].

The well-being and productivity of dairy cows are closely linked to their behavior, with factors such as time of lying and standing, feeding, and movement, which serve as indicators of health and well-being [43]. The main objective of this study was to evaluate and optimize deep learning-based object detection models for automated classification of cattle activity. The authors compared different variants of the YOLOv5 network (v5x, v5l, v5m, v5s, and v5n), learning rates (0.1, 0.01, and 0.001), data pack sizes (4, 8, 16, and 32), and the performance of the optimizer used (SGD and Adam) to identify the most suitable model in terms of accuracy and computational efficiency. The acquired images from a barn with 100 cows were annotated using polygonal masks, and all labeled objects were divided into two classes, cow_stay and cow_lay (Figure 3).

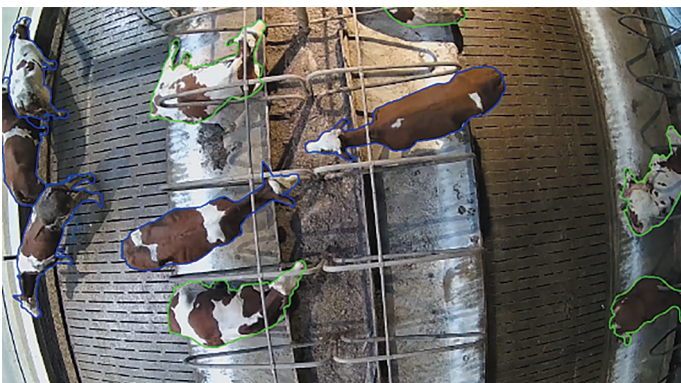


Figure 3. Annotation using polygonal masks with assignment of a specific class (cow laying is contoured with green, and a cow standing is contoured with dark blue) [43]

YOLOv5m showed the best results in terms of time and accuracy optimization, with a ratio of 0.5:0.95 of 0.8969 (compared to 0.9070 for YOLOv5x). The training time for YOLOv5m was 7:48:19, while YOLOv5x required 16:53:27. The highest accuracy (0.9028) was achieved with a learning rate of 0.001, and the lowest (0.8897) with a learning rate of 0.1 [43].

Accurate and timely information on the livestock quantity and location in the farms is difficult to obtain, especially in case of large agricultural enterprises. Livestock counting is primarily done manually, which is labor-intensive and prone to error. Currently, many farmers count their animals approximately once a month, while others only count their livestock when loading or unloading them from trucks, arriving at or leaving the farm. Therefore, many farmers are interested in monitoring their livestock using a reliable automated system. Monitoring the distribution and population of animal species over time is also a key element of successful saving the herd. In this regard, the development of deep learning algorithms and unmanned aerial vehicles (UAVs) is creating a new area of research for remote monitoring and counting of various animal species in various geographic and climatic conditions. In this paper, the authors focused on the detection and counting of sheep in a pen via UAV video. Sheep counting is performed using a model based on regional convolutional neural networks, and the results are then compared with other methods to assess their performance [44].

To improve sheep counting accuracy and avoid mutual occlusion interference caused by different moving speeds among sheep, Chinese researchers proposed a fusion concept between an improved YOLOv5x model based on an attention mechanism and the DeepSort algorithm. The improved, high-precision YOLOv5x model for sheep detection reduces the false detection rate and missed detections. At the same time, the DeepSort algorithm is used to address the problem of sheep that were not counted due to mutual occlusion. Then, in the sorting algorithm, during the target (sheep number) forecast and appearance recognition stages, newly appearing objects after occlusion are distinguished and compared to complete target tracking. In this study, dynamic sheep counting is primarily applied to a single-family sheep farm, where the number of sheep is relatively small, averaging approximately to 50 heads, which is insufficient for generalization to the dataset. Therefore, a dataset-based optimization technique is proposed to address the sample insufficiency problem. That is, low-resolution images collected by a binocular vision sensor are used as input, the SRGAN network model is used for super-resolution reconstruction to generate 500 high-resolution datasets, and then 800 high-resolution images are obtained through autonomous data enhancement and expansion in the form of sheep datasets. The high-resolution images are used as the training dataset of the YOLOv5x-ECA model, which integrates the structure of the ECA channel attention mechanism to adaptively

enhance the channel weight information. In this case, the sparrow search algorithm (Bird Swarm the YOLOv5x-ECA (a bioinspired evolutionary algorithm using swarm intelligence inspired by social interactions and bird flock behavior) algorithm, based on the elite opposition learning strategy, is used to optimize the training speed of the detection model to obtain optimal group weight information for further improvement of performance in sheep recognition. In the experiment, 800 high-resolution sheep images augmented with the SRGAN network and data augmentation are used as the model datasets, and weight information obtained by the YOLOv5x-ECA-SSA* model is used to accurately recognize sheep. According to the DeepSort algorithm, recognized sheep are tracked, forecast, and matched as efficiently as possible. The experimental results show that the testing accuracy of YOLOv5x*, YOLOv5x-ECA*, and YOLOv5x-ECA-SSA* based on SRGAN and training data improvement are 95.74 %, 96.50 %, and 97.10 %, respectively. The error rate of each model when combined with the DeepSort algorithm for completing the dynamic sheep counting is 13 %, 12 %, and 5 %, respectively. Among them, the YOLOv5x-ECA-SSA* model has the highest mAP and the best sheep counting effect. The result can provide a new theoretical method for realizing intelligent dynamic counting and tracking in the grazing process and provide a new technical application for intelligent livestock farming [45].

Tiana et al. [46] proposed a method for automated pig counting using deep learning. The reported convolutional neural network (CNN) model learns the reconciliation of an image object to a density map and obtains the total number of pigs in the entire image by integrating the density map. Accurate pig counting can improve the management of pig feeding, barn construction, etc., which can help farmers reduce costs and unnecessary losses, and make farms more competitive. However, accurately counting pigs is difficult due to pig image occlusion, differences in group density, camera perspective, and lighting variations. Manual counting can easily miss some pigs or add several extra pigs, is time-consuming and expensive, and also leads to the introduction of false data in reports. These problems are common in large breeding enterprises. Deep learning has proven to be the most promising solution to ensure accurate object counting in various environments. The authors of the automated model proposed to use a modified version of Counting Convolutional Neural Network in an end-to-end mode as a homogeneous multi-branch architecture for pig counting. The deep learning architecture combined Counting Convolutional Neural Network (CNN) and ResNeXt, so the proposed model should not depend on the results of image foreground segmentation, as the model only takes into account the appearance information. The results of the study showed that on real-world data, the proposed counting method yields an average absolute error of 1.67, regardless of the pig image, such as those covered with shadows, occlusions, or from

different perspectives. The model's object detection and identification speed is 42 ms, which complies with the requirements of agricultural applications [46].

Automatic identification of individual animals is an important step towards achieving personalized care in terms of disease detection and management, as well as improved feed quality. Marsot et al. [37] propose a new structure consisting of computer vision, machine learning, and deep learning algorithms to offer a relatively low-cost and scalable solution for pig recognition. In the implementation of this project: first, pig faces and eyes are automatically detected by two Haar function-based cascade classifiers and one shallow convolutional neural network to produce higher quality images. The Haar function-based cascade classifier [47] was proposed by Viola-Jones company, and it is trained to recognize the pig face. This solution is preferable to color segmentation because it avoids detecting not only the pig's ears/body but also piglets that may appear in the background. Second, pig face recognition is accomplished using a deep convolutional neural network. Additionally, class activation maps generated by grad-CAM and noticeability maps are used to visually understand how the neural network learns discriminative features. Applying the proposed approach to 10 randomly selected pigs photographed in a farm setting, the proposed method showed its high performance with an accuracy of 83 % on 320 test images. However, by examining the noticeability and activation maps, it was determined that the neural network benefits from interesting features, such as the eyes and specific markings on the pig face, but may be sensitive to parasitic patterns caused by dirt stains or food remains. The results of this study will contribute to the practical application of AI-based animal identification in pig farming [37].

Pen soiling is an undesirable behavior of slaughter pigs that can take place in facilities where pigs are housed in pens with a designated resting area (solid floor) and a designated washing area (slatted floor). It increases farmer labor costs, reduces pig hygiene and well-being, and provides negative environmental consequences. Previous researches suggest that monitoring the positional behavior of weaner / finisher pigs in their pen can be used in early warning systems that can alert farmers about coming pen soiling event 1–3 days in advance. For example, Jensen et al. [48] showed that manual counts of the number of pigs located in different areas of a pen can be used as input to machine learning methods to forecast pen soiling events a day before they occur. In order to make this alert system feasible, monitoring of pig positioning must be automated. One method that can be used for such automation is a convolutional neural network (CNN) with a linear regression output, where the output value is the estimated number of pigs in a given area of the pen. The proposed CNN takes partial images of the pen corresponding to different areas of the pen and outputs the estimated number of pigs in the partial image. In such a model, convolutional layers automatically extract relevant features from the image, and subsequent fully connected

layers then perform further processing before the final numerical output is obtained [49]. Similar CNN concepts and architectures have previously been used to estimate the live weight of slaughter pigs [50].

Sheep producers need to identify different sheep breeds to assess the commercial value of their herd and the cost of sheep raising. DNA testing is an alternative method for breed identification; however, this method is not effective for evaluating large numbers of sheep in real time in a production environment. Therefore, methods are needed that can efficiently and accurately replicate the ability of an expert to identify sheep by breed in a farm environment. To differentiate sheep breeds on a farm for automatic sheep breed identification, the following work steps were completed: setting up a prototype computer vision system on a sheep farm, creating a database containing 1,642 images of sheep of four breeds, labeled by an expert with breed information, and creating a sheep breed classifier using machine learning and computer vision to achieve an average accuracy of 95.8% with a standard deviation of 1.7. The processing time for one image takes on average 0.7 s. To train a sheep breed classifier on a farm, minimal image pre-processing (image resizing and upscaling) was required, as the convolutional neural network (CNN) model was found to be invariant to the sheep's viewpoint, pose, size, or illumination after being trained using the full set of images. Furthermore, the CNN model was able to process images of the sheep's entire body, as well as enlarged images of its face, which contains key information that allows it to distinguish between different breeds. The experiments examined the effect of fine-tuning different numbers of VGG-16 layers (the VGG-16 model is a 16-layer convolutional neural network developed by Visual Geometry Group at the University of Oxford) to analyze its impact on the performance of a sheep breed classifier. A model with six fine-tuned layers showed more stable behavior and higher accuracy of classification than a model with three fine-tuned layers. To determine the best training method for the sheep breeds classifier, two transfer learning approaches were assessed: one by fine-tuning of six VGG-16 layers, and the other using a pre-trained VGG-16 model with an SVM support vectors over it. Training the SVM using features from the pre-trained VGG-16 took twenty minutes, while fine-tuning VGG-16 on the same computer took twelve hours. The fine-tuned VGG-16 model achieved a high average accuracy of 94%, 15% higher than the pre-trained VGG-16. It also showed a lower standard deviation than the second model (1.9 versus 3.9), reflecting the consistency of its results. This makes sheep breed classification highly reliable and practical for use on farms. The developed classifier can help sheep farmers accurately and efficiently differentiate breeds without the need for an expert, ensuring more accurate meat yield assessment and cost management [51].

Growing demand for livestock and poultry products requires new approaches to animal breeding and raising. Breeding programs are currently seeking the ways to in-

tegrate animal behavioral phenotypes, as they are linked to rearing technologies, feeding, health, and animal well-being, and can thus impact animal productivity and the economic benefits of the industry.

Artificial neural networks (ANNs) have been used in poultry farming to solve complex nonlinear problems: problems of management and forecast of economically important traits, such as estimation of egg production curve parameters [52], growth curve of broiler chickens, reproductive performance of poultry and their demand for nutrients [53].

Forecasting the slaughter weight of quails in the early stages of the growing period is cost-effective for producers, given that quail production for meat production is growing worldwide [54]. Therefore, the aim of the study conducted by Jahan et al, was the forecast and optimization of slaughter weight of meat Japanese quails (*Coturnix coturnix*) at the age of 45 days based on their early growth performance, sex, and egg weight as predictors using artificial neural network modeling. The multilayer feedforward perceptron neural network structure was used to build the artificial neural network model [53]. The ANN structure defines the arrangement of neurons in 3 separate layers (input, hidden, and output). Therefore, the input layer outputs the data to the network, the hidden layer processes the data, and the results are extracted in the output layer. From the research results, it was determined that the most suitable network on the input data for forecasting slaughter weight in Japanese quail was identified with 7 neurons in the input layer, 11 neurons in the hidden layer, and one neuron in the output layer. The coefficient of determination (R^2) was 0.9404, 0.9359, and 0.9223 for the training, validation, and testing phases of the system, respectively. According to the sensitivity analysis, the most important input variable for forecasting slaughter weight was body weight at 20 days of age, while less important input variables were bird weight at hatching and body weight at 5 days of age. Among the 7 input variables for forecasting slaughter weight (body weight at 5, 10; 15, 20, 45 days; egg weight; body weight at hatching; body weight at 45 days), bird sex as a discontinuous variable was the second important predictor. Egg weight was the fifth important predictor and even more important than body weight at hatching and weight at 5 days. Moreover, egg weight can be a marker of the quail chicks' health and rate of survival, at least in the early stages of life. To forecast the slaughter weight of Japanese quail, a neural network was trained using the backpropagation algorithm [53].

The objectives of the study, aimed at developing and validating machine learning models for monitoring individual behavior of group-housed broiler chickens, were: 1) developing and optimizing machine learning models for detecting, tracking, and classifying individual behavior of group-housed broiler chickens using continuous video recordings; and to use a set of independent data to evaluate the performance of the developed machine learning model

for differentiating the behavior of individual poultry [55]. Forty-two video recordings (total video duration = 1620 minutes) from 4 different poultry pens were analyzed in developing the machine learning models for monitoring individual behavior of broiler chickens. Four behavior types were classified: feeding, drinking, active (any movement other than feeding and drinking, but including feather fluffing and/or ruffling, pecking at the walls of another pen, scratching, stretching, and floor clawing), and inactive (the bird sits with its abdomen resting on the floor covering or stands with its feet touching any floor covering. The bird's head may be hidden under its wing or be positioned at body level or even lower. The bird may stand without showing any other behavior).

The optimal model was used to continuously analyze an external dataset of 11 videos (duration = 326 minutes), capturing the second-by-second behavior of each individual broiler (16 chickens were used). After comparing model performance, YOLOv5l was selected from five detection models for detecting individual broilers in a pen, as it is the most widely used and reliable object detection model. Pre-trained tracking algorithms were then compared to determine the optimal model. Using the pre-trained codes, 5 different models (osnet_x0_25_msmt17, osnet_x0_25_market1501, osnet_x0_75_imagenet, osnet_ibn_x1_0_imagenet, osnet_ain_x1_0_imagenet) were randomly selected with different data fidelity thresholds of 0.5, 0.6, 0.75, 0.8, 0.9 and 0.95. Based on the study results, osnet_x0_25_msmt17 was selected to track each detected bird in continuous frames; and the Gradient Boosting Classifier, out of 12 machine learning classifiers. Most models were able to retain previously assigned individual chick identities for a limited period of time but lost them over the study period (≥ 4 min). The final system was able to accurately predict the time of feeding (accuracy = 0.895) and drinking (accuracy = 0.9), but underperformed for the time of active (accuracy = 0.545) and inactive (accuracy = 0.505) behavior. The algorithms used by the machine learning models were able to accurately predict feeding and drinking behavior but require improvement in maintaining individual chicks' identities and determining active and inactive behavior [55].

The role of AI in meat tracking at the stages of the technological process (identification/classification/forecasting) of meat products

Meat traceability is important for analyzing the quality of individual meat cuts, including the farmer who produced the animal and the parameters of the technological process from which they were processed to the finished product. RFID tags are currently the dominant technology for food tracking [56,57]. However, RFID tagging of meat at the slaughterhouse has its drawbacks: tags can disappear within the meat product and end up on the consumer's plate, leading slaughterhouses to avoid directly tagging meat cuts, attaching the tag to the device transporting the meat.

Other methods have been proposed for tracking meat cuts. For example, a conveyor belt system capable of tracking meat cuts in a deboning facility has been developed. A disadvantage of this method is that it is prone to cases where identification tags are lost or interchanged between the carrying devices. To simplify cut tracking, it has been proposed to embed RFID chips in the carrier hooks for meat cuts [58]. The possibility of using barcodes printed on the beak and legs of chickens has been studied [59]. This approach is not well suited for meat tracking, as it requires the meat product to have inedible parts suitable for barcode printing. A number of researchers are conducting cattle breed identification when identifying beef based on DNA analysis or are investigating the possibility of using DNA analysis to trace individual cuts of meat back to the original carcass [56]. However, DNA identification is a rather labor-intensive method for slaughterhouse conditions.

The approach proposed by Larsen et al. [56], based on modern computer vision and image processing techniques, resembles DNA identification in the sense that identification comes from the object rather than from a tag attached to the object.

In industrial meat processing plants, individual cuts of meat are hard to track after carcass cutting. A technology for ensuring traceability of individual cuts of meat has been proposed in Denmark, using computer vision and image processing methods for pork loin (211 samples) as an example. For image analysis, the pork loin is photographed in two sessions, separated by a day. The loin samples are subjected to various disturbance scenarios to simulate real-world working conditions at the plant [56]. All disturbances took place after the first and before the second photo session. These disturbances include:

- Rough processing of 19 loin samples, which are heavily dropped and tightly squeezed on the table before the second photo session.
- Incorrect cutting. Additional pieces of meat and bones are cut from 18 loin samples before the second photo shoot.
- Incorrectly hung 19 samples where loins are hung on their sides when stored overnight, thus causing their bowing.
- Illumination and orientation change: Before photographing, 37 meat samples are rotated from 45° to 180° around the optical axis. This creates illumination variations, as the light falls differently on the rotated object. This evaluates whether the proposed image analysis algorithm is invariant to different object orientations.

The objective of the visual meat pattern recognition method is to correctly match images of pork loin between two photo sessions. The image recognition method is divided into four steps: 1. Segmentation. First, the pork loin is segmented. That is, the pork loin is cut out from the pixels of the background image. 2. Canonization. Then, the segmented pork loin images are brought to a canonical

form, which minimizes variability from external sources, such as lighting. 3. Description. From the canonical images we generate a description of the image structure. 4. Matching. The pork loin samples are matched by comparing the descriptors from the previous step. In total, the recognition method takes less than 2 s per one image. The proposed image analysis-based meat pattern tracking method is a promising alternative to more invasive methods currently available [56].

In the meat processing industry, the decision to implement automated or robotic processes is typically driven by return on investment, which in turn typically depends on improved product quality, reduced labor costs, or a reduction in safety incidents [60]. However, beef deboning on modern deboning lines is still primarily a manual operation. Operators at the end of the line identify products, check their quality characteristics, and then manually redirect them to the relevant packing stations.

Meat identification for labeling and quality control on production lines is largely performed manually, which can lead not only to errors in meat labeling but also to bacterial cross-contamination. Artificial intelligence is used in many disciplines to identify objects in images, but these approaches typically require a significant volume of images for training and validation. A study was conducted in a commercial Irish meat processing plant to identify meat by image and weight for its subsequent labeling. Images of 7,987 individual cuts of beef, trimmed of fat and tendons, isolated from *M. semimembranosus*, and their weight data were available for analysis to systematize the experimental data. Various classical neural networks and an integrated machine learning approach were then tasked with identifying each cut of meat; The performance of these approaches was measured by accuracy (the percentage of correct forecasts), precision (the ratio of correctly forecast objects to the number of objects identified as positive), and sensitivity (also known as the true positive rate or sensitivity). Preprocessing and application of deep learning algorithms were implemented using the Python programming language. The new comprehensive approach to meat identification outperformed a number of classical neural networks, including the convolutional neural network (CNN) convolutional neural network) and residual network ResNet. Accuracy, precision, and sensitivity for the new method were 99.13%, 99.00%, and 98.00%, respectively, while the next-best method achieved 98.00%, 98.00%, and 95.00%, respectively. The new integrated approach demonstrated positive results for identifying each piece of meat, with the use of color images improving categorization accuracy compared to grayscale images while also taking into account the product's weight. By collecting and systematizing image and weight data for individual chunks of meat, it is possible to develop a methodology for accurate classification and increased automation of the meat-piece identification process. Improved object detection algorithms and the incorporation of weighting factors

appear to have eliminated the need for infrared spectroscopy and can potentially be used in many other areas of the food industry. The accuracy of the Ensemble machine learning model demonstrates the capability of artificial intelligence to replicate the behavior of a human operator. The resulting algorithm eliminates the need for a human operator, thus reducing the risk of cross-contamination of samples and potentially increasing the shelf life of the product [61].

In South Korea a mobile app has been developed that classifies beef quality using artificial intelligence, which has undergone rapid technological advancement in recent years. The app allows users accessing information, including cut labeling, freshness, and marbling of the beef they are about to purchase. Deep learning technology was used to classify beef cuts, and OpenCV (OpenCV) technology was used to determine quality. Source Computer Vision). The application was developed in a client-server system for real-time operation. The server part of the program is hosted on a website, which contains a module for classifying beef parts, assessing freshness and marbling. The user's (client's) mobile phone takes a photo of the beef and sends it to the server, and the server analyzes the resulting image to identify and determine the quality, freshness, and marbling of the beef. The results are then sent back from the server to the client. The developed system has proven itself effective for tenderloin, sirloin, and ribs. For these types of meat, it provided a high accuracy rate of over 75%. However, for other types of beef cuts, it performed poorly, which is due to the problem of training for image classifiers. The proposed application is designed to help the average consumer make the right decision when purchasing beef by providing data on this beef [62].

To develop a beef cut classification system based on the existing TensorFlow deep learning neural network, we evaluated its capabilities for quickly classifying seven different types of beef cuts (bone-in ribeye steak, boneless ribeye steak, chuck roll steak, flank steak, striploin steak, short ribs, and tenderloin). Color images of the beef samples were obtained using a laboratory computer vision system and collected from an internet platform Google Images. In total of 1,113 images of beef cuts were used as training, validation, and test datasets. A model developed using a deep learning neural network algorithm was able to classify specific cuts of beef (flank steak and tenderloin) with 100% accuracy. Two pre-trained neutral convolutional network (CNN) models, Visual Geometry Group (VGG16) and Inception ResNet V2 was used to train, validate, and test these models for classifying beef images. Image augmentation was incorporated into the neutral convolutional network models to avoid re-learning issues, resulting in improved image classifier performance. The VGG16 model outperformed the model Inception ResNet V2. The VGG16 model, combined with data augmentation technology (data augmentation method), was able to achieve a high accuracy of 98.6% on 116 test images, while Inception ResNet

V2 achieved a maximum accuracy of 95.7% on the same test images. Based on the performance of both models, the deep learning technology clearly showed promising prospects for identifying beef cuts in the meat industry [63].

García-Infante et al. [27] have tested artificial intelligence algorithms for classifying commercial lamb meat categories. The dataset used in this study was obtained from 78 indigenous *Mallorquina* lambs. The samples were classified according to production model and commercial categories as follows: milk-suckler lambs (SL; $n = 30$); light lambs (Ternasco) (TP; $n = 26$), which were reared with their mothers on the natural pastures of the Balearic Islands, including natural pastures and pastures of oats, ryegrass and barley, and on cultivated pastures as green forage during the spring months; and Ternasco TC ($n = 22$) lambs, that were reared with their mothers on cereal crops and natural pastures on the Balearic Islands, including oats, ryegrass and barley pastures as the source of green forage for two months. The performance of six machine learning algorithms of artificial neural network (ANN), decision tree, k-nearest neighbors (KNN), naive Bayes (NB) function, multinomial logistic regression (MLR), and support vector machine (SVM) were evaluated for their ability to perform descriptive data analysis and classification tasks using various types of raw data. Each algorithm was tested on three datasets, namely, sensory and sensory attributes (CIELAB color, water holding capacity, Warner-Bratzler shear force, volatile content) and nutritional attributes (raw composition and fatty acid profile). The evaluated algorithms demonstrated overall accuracies ranging from 0.88 (ANN) to 0.54 (KNN) in classifying those three lamb categories. Among the six tested algorithms, ANN demonstrated the highest performance in processing the organoleptic and sensory meat dataset, achieving an overall accuracy of 0.88. In fact, the overall accuracy of the ANN was 24–39% higher than the results obtained with the other tested algorithms. Furthermore, the ANN algorithm was able to automatically adjust internal parameters to improve forecast accuracy. Based on these results, it can be concluded that the use of machine learning algorithms is an effective alternative for differentiating the meat of native Spanish lambs. Further research aimed at improving classification methods based on machine learning will be useful for lamb meat authentication and quality certification [27].

Machine learning algorithms are widely used to forecast carcass yield. Deep Learning (DL) has proven its being successful in solving many image classification problems, particularly for forecasting bovine carcass yield and comparing these forecasts with methods of standard machine learning (ML). The following approaches were selected as DL methods: (1) animal phenotypic data used as features for a number of machine learning algorithms, (2) carcass images used to train convolutional neural networks, and (3) analysis of carcass dimensions measured directly from carcass images, combined with corresponding phenotypic data and used as feature data for the machine learning al-

gorithms. The final approach to forecasting grouped carcass cuts included 346 carcass dimension measurements at predetermined image points and recorded across all digital images. One of the key findings of the study is that the difference in performance between DL and ML models is insignificant. From a practical standpoint, trained DL models are easier to use than ML models. This is because DL models only require carcass images captured at the slaughterhouse within a few minutes after slaughter. In contrast, machine learning models require significantly more data collection [64].

Traditional approaches to forecasting pork quality parameters have relied primarily on statistical methods such as regression analysis [65]. However, these methods exhibit significant limitations in both forecasting performance and practical applicability. The main limitations of existing studies on pork quality forecast can be summarized by the following criteria: (1) focusing on specific time points rather than the dynamic changes; (2) reliance on single algorithms rather than ensemble approaches; (3) limited incorporation of multivariate data, including genetic and feed information; (4) insufficient sample sizes and genetic diversity; and (5) inadequate integration of the chemical mechanisms underlying quality development with forecasting modeling approaches [66]. Artificial intelligence-based ensemble quality forecast models achieve high accuracy in forecasting dynamic changes in pork quality [67]. Based on experimental data obtained from 1,284 pigs of 24 breeds, Chinese scientists developed and optimized ensemble machine learning models, including LightGBM, XGBoost, and Random Forest, which takes into account the biochemical mechanisms governing pH changes and color development in pork meat within 48 hours after slaughter. The proposed collective learning method achieved high forecast accuracy: R^2 values exceeded 0.7 for both pH and color parameters. Although meat quality parameters generally stabilize for 24 hours after slaughter, forecasting quality within 48 hours possesses significant practical value for commercial meat processing and distribution. For example, early forecast of quality parameters within 48 hours allows processors to determine which products are suitable for premium processing, which are optimal for fresh market sales, and which may require promotional pricing. This forecasting decision-making capability is critical for optimizing supply chain management and maximizing product value. Therefore, the development of accurate 48-hour quality forecast models possesses significant commercial value. Trait importance analysis identified early pH values and muscle structural characteristics as critical predictors consistent with key biochemical processes such as anaerobic glycolysis, protein denaturation kinetics, and myoglobin redox reactions, confirming the complex interplay between chemical mechanisms in meat and sensory traits, providing an accurate alternative to traditional assessment methods. The established chemical basis for forecasting pork quality offers a scalable framework

for integrating genetic, environmental, and technological factors, ultimately improving the accuracy of quality control and sustainability in meat production through the application of food chemistry principles [67].

In [68], an analysis of a multi-component meat system (pork and “Doktorskaya” cooked sausage) was performed using a convolutional neural network (CNN) with two convolution layers (convolutional, C-layer) and pooling (subsampling, S-layer). The gradient backpropagation algorithm was used to train the CNN. The authors determined the main microstructural characteristics (classification parameters) for identifying plant components in raw meat and finished products using CNN. The concentration of plant components and their nature (carrageenan, starch, soy isolate, vegetable gum) did not matter; the CNN identified them regardless of concentration. The best result was obtained using the ReLu activation function (0.9843), followed by the SoftPlus (0.9765) and eLu (0.9687) activation functions.

The study [69] demonstrates the capabilities of AI in recognizing the undeclared components in histological sections of raw meat. A study of digital images of histological sections of raw meat using five optimization algorithms (Adam, NAdam, FTRL, Adamax, AMSGrad) included in the TensorFlow pack revealed that the NAdam algorithm demonstrated the best results in recognizing/identifying the undeclared herbal preparations among protein substance. Recognition accuracy on the test sample was 80%. Classification metrics: AUC = 94%, Recall = 78%, Precision = 79%.

A comparative analysis of the capabilities of the YOLO and ResNet convolutional neural networks in recognizing undeclared components in histological sections of raw meat using the NAdam optimization algorithm was conducted in the study [70]. The study found that both ResNet and YOLO convolutional neural networks both possessed equally high potential for identifying undeclared components in raw meat. Both demonstrated virtually identical results in the accuracy of recognizing/identifying undeclared components in images of histological section.

AI in meat products authentication

Confirming the authenticity of meat and meat products is becoming increasingly important due to the spread of food adulteration. Meat adulteration, such as deliberate adulteration or mislabeling of meat varieties, undermines the meat market by causing consumers’ mistrust. These fraudulent actions affect both consumers and producers of authentic food products. This phenomenon represents an information asymmetry that the market is not able to correct spontaneously and on its own. Meat authentication methods are crucial for market legitimacy and, thus, ensuring fair trade.

Meat authenticity and traceability are issues of the highest importance in modern society, as evidenced, for example, by widely publicized events involving the adul-

teration of meat products with undeclared meats, such as horse meat [71]. This underscores the demand of consumers worldwide for clear and reliable information about the food they consume. This is particularly true for processed meat products, where simple visual inspection cannot readily distinguish the various components as is the case with intact fresh meat. More than ever, consumers are focused on the link between food and health, seeking reliable information about the safety, quality, composition, and origin of food products. Food authenticity has become a key issue in the production chain [72].

The aim of the research work by Brazilian scientists was to obtain classification models for the authentication of beef cuts from animals raised under fully controlled conditions of genetics, nutrition, and geographic origin, using multi-element profiling and supervised learning algorithms. The feasibility of combining classification algorithms was assessed based on the content of the main microelements: Br, Co, Cs, Fe, K, Na, Rb, Se, and Zn, selected as a tool for the authentication of beef cuts [73].

To build classification models based on the multi-element beef profile determined using neutron activation analysis, the following were used: classification and regression tree (CART); multilayer perceptron (MLP), widely used in deep learning technologies; naive Bayes classifier as a probabilistic machine learning algorithm based on Bayes’ theorem and used in different classification problems (NB); random forest (RF) method — machine learning algorithm for solving classification and regression problems; and sequential minimal optimization (SMO) — an algorithm for solving the quadratic programming problem. The classification accuracy values obtained for beef cuts were 96% (MLP), 95% (SMO), 91% (RF), 86% (NB) and 70% (CART) [73]. The multilayer perceptron (MLP) algorithm provided the best classification for the authentication of beef cuts based on the content of major and trace elements, as it provides the best accuracy, sensitivity and specificity of the classification.

Recently, spectroscopic methods of hyperspectral imaging (HSI) systems have been used to identify meat and meat product types. These methods allow for the simultaneous receiving of both spatial (textural) and spectral information from meat product samples. The main advantage of the line-scanning HSI system is that it provides a wide spectral range. However, image acquisition with line-scanning is slow, and the image size requires large computational resources. To mitigate these drawbacks, a new deep 3D convolutional neural network (3D-CNN) model for extracting combined features and subsequent identification of red meat (lamb, beef, pork) in the HSI image and the innovative graph-based post-processing method to improve the forecast of the 3D-CNN approach were proposed [74].

During the study, meat samples were randomly divided based on meat species and product type into training set and test set: a set of 105 meat samples was used for training purposes, including the processes of training and selecting

(or validating) the best model. An independent set of 79 meat samples was used to obtain the final quantitative and qualitative results (i.e., accuracy and classification maps). This experimental design was used to ensure that the analysis was independent of the influence of the training and experimental processes. The results show that the deep learning 3D-CNN approach for red meat classification by combining spectral and spatial features of HSI data of red meat products significantly improved the overall accuracy of state-of-the-art models. Despite the limitations in spectral information when processing HSI imagery, the 3D-CNN model demonstrates its reliability in red meat classification with an overall accuracy of 96.9% and 97.1% for HSI images in the near-infrared range (NIR) and visible (VIS) range, respectively. The conducted study allows for further development of researches in the field of real-time red meat authenticity verification and mobile HSI systems using HSI snapshots and deep learning models [74].

A study was conducted in China to identify a specific counterfeit product — adulterated lamb or beef slices used in hot pot, a dish cooked from duck and fat. The goal is to develop a quick and convenient authentication method that customers could use directly in the restaurants [75]. A large number of adulterated lamb or beef slices exist, which are made from duck meat and lamb or beef fat [76] due to their low price. Compared to other cheap meats, such as chicken, the color of duck meat is closer to red meat. This product is sold legally on the market under labels such as “Meatloaf” or “Stuffed Meatloaf.” Manufacturers of these products have their own secret methods to make these meatloaves visually resemble lamb rolls. Due to the lamb fat content, these meatloaves taste somewhat like lamb. Dishonest hot-food restaurants buy those meat products and serve them as “lamb cuts”. The same applies to adulterated beef cuts. Therefore, it would be advisable to provide restaurant customers with a convenient authentication tool so that such meat fraud can be reported right at the spot [75].

The task of authenticating meat slices in developing a detection method for the aforementioned counterfeit product was formalized as a classification problem of RGB images as input using the textural features of meat slices. Authentication is performed quickly and non-destructively. The only device required is a mobile phone with a camera. For this purpose, a lightweight (and therefore highly efficient) convolutional neural network architecture called MTx-Net was created. Fourteen convolutional layers in four blocks were used to extract reliable visual features. The neural network utilized techniques such as residual values, depthwise convolution, dropout, and batch normalization. A total of 77,956 meat images were collected using 225 kg of meat for training and testing the neural network. This method provides identification accuracy of 99.38% and 98.20% for lamb and beef slices, respectively [75].

Kozan et al. [77] developed and tested a mobile application for meat freshness assessment using deep learning technology. The main focus was on the system methodol-

ogy and validation of the obtained results. A “black-box” testing method was used to evaluate the functionality. This approach allows for checking the system’s functionality from the end user’s perspective, without taking into account its internal implementation, which increases the relevance of the assessment for practical use. Testing included processing images of fresh and spoiled meat in the environment Google Teachable Machine. The classification results demonstrate the system’s ability to identify the product state correctly (Figures 4, 5).

The mobile app interface is presented as a user-friendly tool that visualizes the analysis results directly on the device screen (Figure 6). To verify the results obtained in Google Teachable Machine, the deep convolutional neural network ResNet-50 was used.

Song et al. [78] used a mobile phone front camera and screen to form a “hyperspectral imaging” system to detect adulteration of ground beef with pork based on smartphone videos recorded in a sequence of different colors. For the study, ground beef samples were mixed with ground pork in the range of 10–100% (weight) with 10% weight increments. Light of different colors was generated on the smartphone screen and used to illuminate the sample surface. Short videos were recorded and converted into spectral-like data through image processing. Data samples were collected under different conditions in terms of smartphone type, recording, distance, and lighting conditions, resulting in seven datasets. A partial least squares regression model was used to forecast the adulteration level, yielding coefficients of determination of 0.73–0.98 and root mean square errors of 0.04–0.16. Furthermore, smartphone videos were used to map the prevalence of adulteration levels. The results demonstrate the potential of a simple and inexpensive approach to detecting adulteration in ground meat. The video-based approach to detecting adulteration is more user-friendly in terms of cost and data collection. Therefore, it can be used as an effective tool for processors and regulators for the preliminary detection of adulteration in ground meat [78].

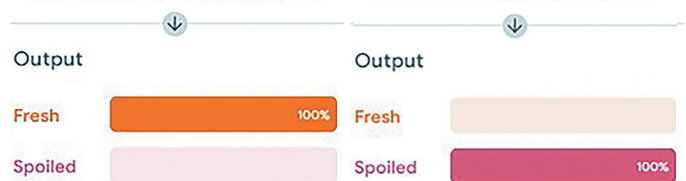


Figure 4. The result of the test classification on an image of fresh meat [77]

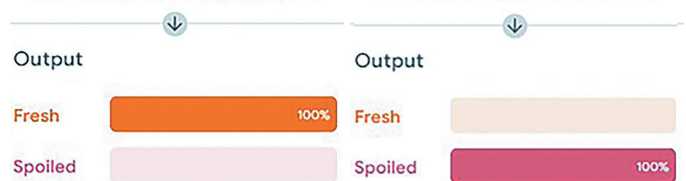
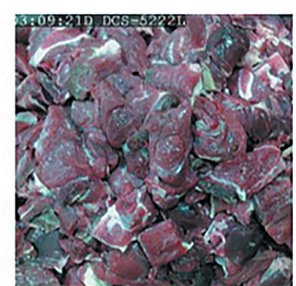


Figure 5. The results of test classifications on images of spoiled meat [77]

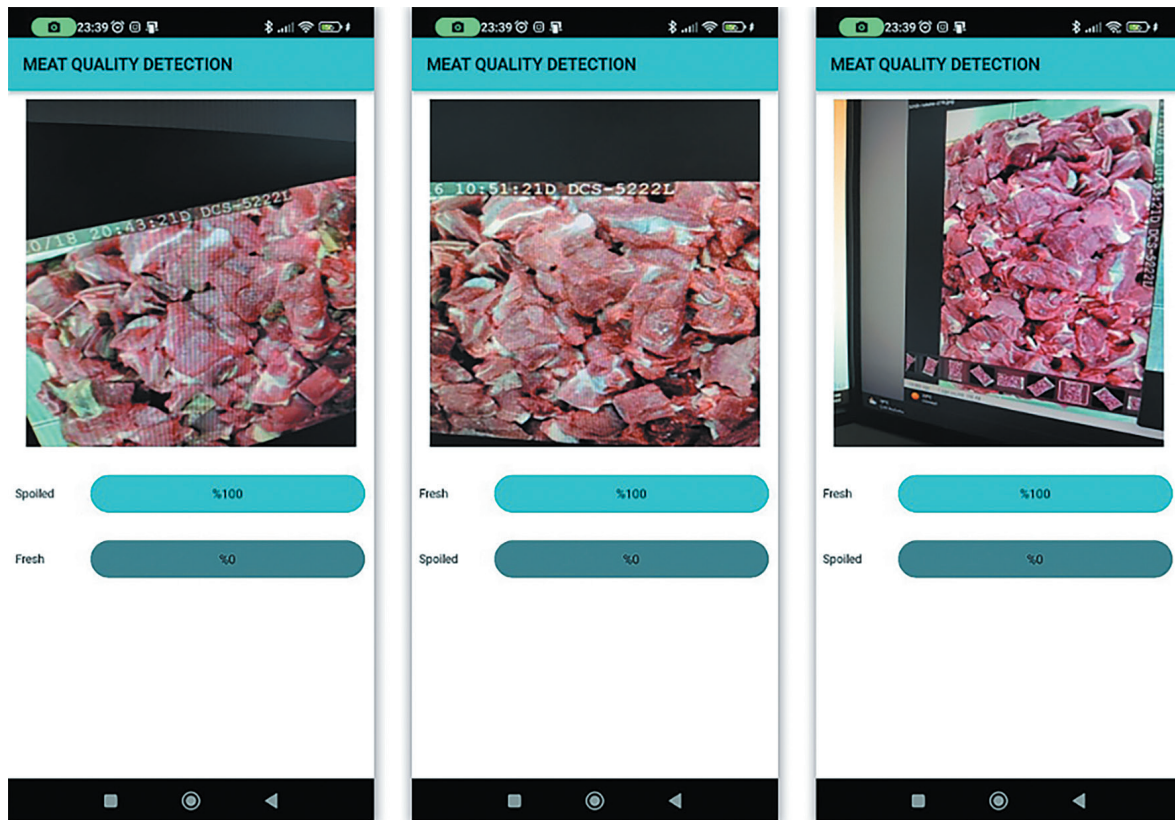


Figure 6. Screenshots from the mobile application developed for this testing [77].

It should be noted that research into detecting meat adulteration has made significant progress by combining the use of electronic noses and artificial intelligence methods. Han et al. [79] developed a low-cost electronic nose using colorimetric sensors to detect pork adulteration in beef, with the extreme learning machine model outperforming traditional methods (91.3% and 87.5% on training and test sets). Furthermore, Huang and Gu [80] presented a combined one-dimensional convolutional neural network (1 DC NN) and random forest framework (RFR) for quantitative detection of pork-adulterated beef with the help of 10 different MOS sensors as an electronic nose. The determination coefficient (R^2) for this model was estimated to be 99.7%.

Assessing the quality and safety of meat and meat products using artificial intelligence technologies

Ensuring food safety is the most important and critical requirement for any food industry, as spoiled food gives the rise of foodborne illnesses. Meat and meat products become contaminated due to various factors, plus frequent human handling on the production line increases the risk of contamination. Growing demands for meat products to meet high quality and safety standards have led to the development of technologies that enable accurate, rapid, and more objective quality assessment. Machine vision technology matches the functions of human vision through electronic image perception and evaluation and can be used for quality assessment and classification of meat and meat products [31].

With the rapid development of computer technology, non-destructive testing systems based on image process-

ing and machine vision have been widely used to obtain product characteristics based on image analysis and recognition of characteristics related to determining the quality and safety of meat products.

The review article [80] is devoted to the possibilities of using ANN. A special role in the work is given to convolutional neural networks, structured like the visual cortex of the brain. In recent decades, CNNs have achieved great success in image recognition, since they are able to concentrate on a small area and highlight important features in it. The prospects for using ANNs in the food industry for incoming quality control of raw materials are noted. In world practice, various methods of remote control of raw materials are used, for this purpose mainly devices based on ultrasound scanning are used. Such devices and analysis systems run control of raw materials based on the ratio of meat tissues (muscle, connective, fat) in a carcass or half-carcass, without affecting the structure of tissues, and do not conduct quality assessment at the cellular (microstructural) level. It has been established that the structure of muscle tissue (diameter of muscle fibers, preservation of cellular elements, tissue porosity, integrity of muscle fibers) reflects the quality of the raw material, its thermal state [81].

Machine vision systems operate by capturing an image of an object, such as a piece of meat, processing the image to measure desired parameters, and comparing these parameters. Parameters with predetermined inspection criteria help inform decisions about corrective actions for the object or production process. The most important advantage of meat inspection using a machine vision system is its

non-destructive nature when examining a meat sample. Recently, there has been significant growth in the use of machine vision in various fields, such as poultry carcass inspection, weight forecast, beef color determination, tenderness forecast, and chemical component forecast of meat and meat products. However, certain disadvantages of this method should be noted. MV technology requires uniform illumination and calibration. It is often difficult to separate overlapping objects from the background when it is necessary to assess both sides of a meat product [31].

Color characteristics are considered one of the most important indicators for assessing the quality of meat and meat products. The first and most important quality assessment any consumer makes before purchasing a food product is color. Rahman et al. studied the ability of computer vision technology to forecast the quality characteristics of beef and concluded that the highest forecast accuracy was obtained for lightness (L^*), average for redness (a^*), pH, moisture loss, protein and ash content in a beef sample [82]. Chmiel et al. [83] investigated the color parameters using image analysis technology to identify PSE in pork. The color parameters were assessed using computer vision systems (CVS) and the CIE — $L^*a^*b^*$ scale. The obtained correlation and determination coefficients between the color parameters characterized by lightness reached low values of 0.44 and 19.4 %, respectively [83].

The efficiency of using a computer vision system (CVS) to calculate the color characteristics of beef and pork meat compared to experimental color data obtained with a Minolta colorimeter revealed significant differences in color parameters ($L^*a^*b^*$, hue change angle, and chromaticity) between the two different methods. The CVS methodology produced colors very similar to visual tests, unlike the Minolta colorimeter. The match rate of colors obtained by CVS with actual meat colors, as judged by trained experts, was 100 %. These results indicate that CVS may be an excellent alternative to the traditional Minolta colorimeter, as it provides higher sensitivity and accuracy. In addition to objective color measurement, computer vision offers other capabilities that may be useful for further quality control or research in the meat industry [84]. Thus, the advantage of CVS is that it determines the L^* , a^* , b^* values for each pixel of the meat sample image, providing speed, accuracy, objectivity, efficiency and allowing the identification of meat quality defects PSE or DFD [83,85], or for forecasting the color and marbling of pork and beef [86].

Researches were conducted to evaluate the quality of pork loin using online computer vision. Eighteen color images of pork loin, images of intramuscular fat (IMF) content, and 88 texture images were used as input indicators for pork quality forecast models. To evaluate loin color, measured color scores were divided into six groups according to a specific range of lightness (L^*) values. For marbling, objective scores were divided into ten groups according to the range of fat content (CF%) values. Based on the research results, an artificial intelligence-based

forecasting model (support vector machine (SVM)) was developed for determining pork quality based on color and marbling, with the highest forecast accuracy of 92.5 % and 75.0 %, respectively. This machine learning method has great potential for forecasting pork loin product quality. However, further research is still needed before a computer vision system (CVS) with artificial intelligence and SVM modeling can be used in pork processing plants. First, it is necessary to optimize the model's performance to achieve higher forecast accuracy rates, and also to select the most effective type of learning algorithm to use. In this study, the kernel radial basis function (RBF) was used, as it is the most common function used for the SVM forecast method. However, there are other learning algorithms that are worth testing and comparing to validate the model's forecast results [86].

Mortensen et al. used a 3D computer vision camera to calculate the weight of broiler chickens with an accuracy of 92.2 % [87]. Moral et al. [88] investigated the potential of image analysis for automated quantification of intramuscular connective tissue in meat and found that its application allows for automatic, accurate, objective, and reliable determination of the amount of intramuscular connective tissue in meat and fiber contraction in muscle. The software they developed allows for the analysis of 20 images per minute and provides more accurate measurements than traditional morphometric methods [88].

Research has identified the potential of computer vision technology for assessing the color of fresh pork loin. Software was developed to segment pork loin images into background, muscle, and fat. Color features were then extracted from the segmented images. This study utilized characteristics such as the mean and standard deviation of red, green, and blue bands within the segmented muscle region. To assess the color characteristics of lean meat, sensory ratings of pork loin were collected from a trained panel using a 5-point color scale and compared with data of computer images analysis. Both statistical and neural network models were used to forecast color gamut using image characteristics as input. The statistical model used partial least squares to derive latent variables. The latent variables were then used in multiple linear regression. The neural network utilized a backpropagation learning algorithm. The correlation coefficients between the forecast and original sensory scores were 0.75 and 0.52 for the neural network and statistical model, respectively. The forecast error was the difference between the mean sensory score and the forecast color score. An error of 0.6 or less was considered insignificant from a practical point of view. For 93.2 % of the 44 pork loin samples, the forecast error in the neural network modeling was less than 0.6. In addition, 84.1 % of the samples yielded a statistical forecast error of less than 0.6. The results of this study showed that the image processing system combined with the neural network is an effective tool for assessing the color of fresh pork [89].

Liu et al. investigated the feasibility of using a computer vision system to forecast the percentage of intramuscular fat in pork and developed a stepwise regression model and a support vector machine (SVM) model. The accuracy rates of the regression models were 0.63 for stepwise regression and 0.75 for the support vector machine [90].

Pork color is crucial for assessing its safety and freshness, and traditional human-eye observation methods are ineffective and subjective. In recent years, several methods based on computer vision and deep learning have been proposed that can provide objective and stable assessments. To improve the performance and accuracy of this method, which was limited by the lack of effective preprocessing of background noise, a standardized pork image acquisition device was developed by processing 1,707 high-quality pork images, and a new deep learning model for color forecast was proposed. The deep learning framework, called Porkolor, consists of two modules: an image preprocessing module and a pork color classification module. The image preprocessing module uses the Segment Anything Model (SAM) was developed to extract pork patterns and remove background noise, thereby improving the accuracy and stability of the model. The pork color classification module uses a ResNet-101 model trained with a patch-based learning strategy as a baseline. The resulting model achieved 91.50 % classification accuracy on a high-quality pork image dataset and 89.00 % on an external validation dataset. A POPO color features dataset was also created to address the current lack of a large-scale, publicly available pork color classification dataset. The pork color classification system operates as follows. First, an image of pork captured by an image collector is sent to SAM, and the trained SAM generates several pork pattern masks and relevant confidence scores. The mask with the highest confidence score is selected for segmentation, resulting in a clear segmented image of the pork piece. The segmented image is then fed into a trained patch-based ResNet-101 network to obtain the final pork color estimate. However, the authors of the study note that their work has some limitations. First, although the POPO dataset is a valuable resource, its size is relatively small compared to other large-scale datasets, which may limit the generalizability of the proposed image analysis model. Second, the annotation process, although thorough, is inherently subjective and may introduce some level of bias. Finally, the performance of our model, like many deep learning models, depends on the quality of the input data. Any deviations in the standardized image collection process may impact the accuracy of the model [91].

In the food industry, risk assessment is a fundamental component of efficient food safety management, which involves a systematic approach to identifying, assessing and controlling potential hazards that may compromise food safety at various stages of the food supply chain.

Traditional food safety risk assessment is primarily performed manually using methods such as HACCP and quantitative microbial risk assessment (QMRA) [24,92].

However, these methods face several challenges: difficulty integrating different data sources and efficiently processing heterogeneous information; reliance on expert knowledge limits their ability to forecast emerging risks; and lacking real-time adaptability, making it difficult to track rapid changes in food production and distribution. These limitations highlight the need for advanced technologies such as machine learning (ML) to improve the accuracy and efficiency of risk assessment. Unlike traditional methods, machine learning can automatically detect and predict foodborne hazards by extracting patterns from data, integrating information from multiple sources, and dynamically adapting to new risks, making assessments more effective and proactive [93].

Rapid and accurate detection of foodborne pathogens in lamb using shortwave infrared hyperspectral imaging (SWIR-HSI) is essential for ensuring the safety of lamb and its products, as well as consumer health. The feasibility of using SWIR-HSI to determine contamination status and *Escherichia coli* (EC), *Staphylococcus aureus* (SA) and *Salmonella typhimurium* (ST) species detected on lamb. The potential of combining SWIR-HSI with traditional machine and deep learning methods for the effective detection of lamb contamination with pathogenic microorganisms was investigated. Hyperspectral images of uncontaminated and contaminated lamb samples with different concentrations (10^8 , 10^7 , 10^6 , 10^5 , 10^4 , 10^3 and 10^2 CFU/mL) of EC, SA and ST were obtained. A one-dimensional convolutional neural network (1D-CNN) model was created and the influence of structural hyper parameters per model. The best full-range model was the 1D-CNN model with 16.64 convolution kernels and a tanh activation function (hyperbolic tangent), installed using the original spectra, and its accuracy on the training set, test set, and external validation set were 100.00, 92.86, and 97.62 %, respectively. The optimal simplified model was the genetic algorithm optimization using the support vector machine (GA-SVM). For pathogen species recognition, the accuracy of the SVM models fitted using the full-band spectra preprocessed with 2D and all 1D-CNN models with the convolution kernel number (16.32) and the tanh activation function was 100.00 %. The researchers noted that the performance of the deep learning model was higher than that of machine learning. This study highlights the importance of developing fast and reliable methods for detecting foodborne pathogens that are tailored to the specific food characteristics [94].

The potential of a computer vision-based method as an intelligent, non-destructive, and robust online freshness forecast method for chicken meat is discussed [95]. The proposed method includes the following steps: image capture, image pre-processing, image processing, computational pipelines, feature extraction, feature selection using a hybrid of a genetic algorithm (GA) and an artificial neural network (ANN), and forecast using ANN. A total of 3000 images of chicken thigh meat (with bones, skin,

and muscle tissue) from both sides (with skin and skinless) were acquired. Images were received every 6 hours for 300 hours long.

Mean square error (*MSE*) and correlation coefficient (*R*) were used as statistical indices to evaluate the performance and accuracy of the network. An *R* value greater than 0.9 indicates high model performance, an *R* value within the range from 0.8 to 0.9 characterizes adequate performance, and an *R* value below 0.8 demonstrates unacceptable performance of the model [96]. High model performance was confirmed by a correlation coefficient of 0.98734 and an *MSE* of 0.002045. The *MSE* of the selected model at the forecast step was 0.002045 h (0.1227 min), which confirms a reliable match between the forecast and actual values for all considered time intervals for determining chicken meat spoilage indicators. Thus, the results of the study indicate a high potential for using GA-ANN computer vision as a reliable, fast, non-destructive and online method for assessing the freshness of chicken meat [95].

Integrating sensory assessment with sophisticated machine learning models is an effective approach to solving various problems [97–100], especially in the field of food quality assessment and safety monitoring [79,101].

An off-flavor, such as boar odor, is primarily associated with the presence of androstenone and skatole and which can indicate poor meat quality. Meat odor profiles vary significantly over time, influenced by natural hormonal processes, gut bacterial metabolism, feed type, breed, age, sexual status, environment, and maturing/decomposition of the meat. Therefore, the development of detection methods that capture dynamic changes in odor profiles is essential for improving the accuracy and reliability of meat quality assessments and provides cost-effective, practical solutions for enhancing safety measures [102].

Swedish scientists have developed a reliable, accurate, and non-invasive method for the rapid detection of chemical contaminants in meat. Initially, they conducted studies to distinguish between the odor of fresh pork and samples with an odor similar to urine, using urine as the chemical contaminant. The study also examined another important aspect of meat quality: assessing freshness during storage of pork for 1 to 31 days at $+5 \pm 1^\circ\text{C}$. Using an electronic nose based on a metal oxide gas sensor with Optimizable Using Ensemble ML models, the proposed method achieved a sensitivity of 96.5 % and a specificity of 95.3 % in categorizing fresh and urine-contaminated meat samples. The model demonstrated robust forecasting performance with Kappa value of approximately 0.926, indicating near-to-perfect agreement between forecasts and actual classifications. The high sensitivity of e-nose to detect volatile organic compounds (VOCs), combined with the high forecasting power of the developed ML models and consensus-based decision algorithms, enabled not only accurate classification of urine-contaminated meat with a validation accuracy of 95.9 % and a test accuracy of 96.3 % but can also be used to quickly determine meat shelf life in real

time as an indicator of meat freshness. The model demonstrated the capability to distinguish between fresh pork meat and meat aged for 1 to 2 days with an accuracy of up to 93.5 %, as well as to identify meat with a storage period of 3–31 days and 17–31 days [102].

Artificial intelligence in meat processing and meat product manufacturing

Primary processing of livestock, including stunning, butchering, evisceration, abdominal dissection, and other operations, is an extremely critical step, requiring high standards of hygiene, quality, and precision to ensure proper subsequent operations [103]. A high degree of automation in the meat industry can be achieved for repetitive technological tasks. For example, the initial stages of meat processing on the slaughter line have undergone significant automation.

With the growing use of machine vision in meat analysis and livestock identification, robots powered by machine vision have been explored. Based on a genetic algorithm, Liu et al. [104] proposed a flexible robotic system for cutting the pig abdomen while hanging it by the hind legs by the hooks, based on an algorithm using trajectory planning: a 2D camera captures the side view of the pig, and a programming platform with the Matlab application package identifies the curve of the pig abdomen from the image, which is fitted with a spline of fifth-order. Then, the trajectory is optimized using a genetic algorithm, minimizing the cutting segments and errors. The optimized trajectory is divided into six segments with a maximum cutting error of 1.6 mm, which ensures accurate cuts of the skin and muscles and avoids damage to the internal organs. The system proved that machine vision is suitable for optimizing the cutting of the pig abdomen [104]. However, the recognized accuracy of this automated cutting system is still low [103]. Methods such as deep learning and 3D modeling can provide higher accuracy than machine vision and offer increasing opportunities for the creation of robotic systems of meat processing [103].

Based on the New Zealand sheep carcass segmentation specification, Mu et al. [105] developed a segmentation robot for cutting sheep carcasses. An image processing system based on Deeplab v3+ networks was used to determine the location of ribs and spine. A 3D camera was used to obtain an image of the sheep carcass depth, and deep image processing algorithms were used to obtain key points of cutting [105].

Another method for cutting sheep carcasses based on a 3D machine vision system with a dual robot system was proposed by Bao et al. [106]. The dual-robot system consists of a 3D scanning system, a sheep carcass fixation device, and a cutting robot. A 3D model of the sheep carcass was constructed using a 3D scanner. The cutting pattern of the cutting robot was planned based on the processed 3D points clouds. The fixed carcass fixation device is designed to prevent the carcass from swinging during the cutting

process, and the dual-robot system performs precise cutting according to the trajectory calculated from the spatial coordinates of the 3D point cloud. The system proposed in this study can improve the efficiency and accuracy of sheep carcass cutting [106]. These methods have shown promising results, which are able to improve the efficiency, accuracy, and consistency of processing while reducing labor costs and improving the workers' safety [105].

An alternative approach to creating automated single-cut deboning systems is to create a human-machine interaction platform — using a robotic arm to assist manual cutting to improve efficiency and reduce the risk of human injury. Research has been conducted on replacing the human hand with a robotic arm for deboning operations by learning the motions from the butcher during meat processing [103]. Wei et al. [107] developed a robotic arm to replace the human hand for ham deboning. The robotic arm consists of a reconfigurable palm and four fingers that perform abduction, flexion, and extension, with the palm configuration adjustable for different tasks and changing conditions. The operator's left hand motion trajectories were recorded using instrumented gloves with associated force/torque and position sensors to map the deboning operation workspace to the robotic hand joint space and perform the deboning operation by both humans and robots. However, some critical issues, such as reducing tendon-driven hand friction and increasing friction at the contact point between the meat and the robotic arm, still require further research [103].

Electrical stimulation technology improves the texture and flavor of meat by using electrical current to stimulate muscle tissue after slaughter. Simmons et al. [108] developed a computer expert system that allows the stimulation parameters (electrical stimulation parameters, intensity and duration) to be adjusted to the characteristics of a specific beef or lamb carcass as it moves along the production line, and to forecast the final pH value and meat temperature.

The effectiveness of the sterilization process is determined by the temperature and duration of heating, the pressure in the autoclave, and the properties of the product. Chung et al. [109] developed a fuzzy logic controller that can maintain the sterilization temperature with an accuracy of $\pm 0.5^\circ\text{C}$ throughout the sterilization duration, adapting to process variations in the autoclave. Precise temperature control coupled with online updating ensures that food products are heated at the set temperature for the expected time and, therefore, successful sterilization. Sterilization is controlled by a programmable logic controller (PLC), which is remotely controlled by SCADA system. The SCADA system monitors the controller's operation and sterilization response and, accordingly, calculates and updates the sterilization duration value (F_0) in real time. The temperature control system must adapt to process variations caused by periodic pressure releases. Compared with sterilization using the traditional F_0 — calculation

method, the proposed system allows for batch processing with less time, less steam consumption and less risk of over-sterilization [109].

Drying is one of the most important step in extracting moisture from meat to achieve the desired moisture level. This process prevents spoilage and impacts product quality, safety, and overall production efficiency. Traditional approaches to drying time estimation are often based on rules of thumb or manual observations, which can be labor-intensive, subjective, and prone to human error. Therefore, implementing an automated solution by developing a meat drying time forecast model is essential for optimizing the product lifecycle. Taking into consideration the potential of machine learning algorithms, they have demonstrated promising results in recent years in solving various forecasting problems. Building on this, research was conducted to explore the use of machine learning methods to forecast the drying time of meat-based food products, taking into account multiple factors, including product structure and properties, environmental parameters, drying chamber characteristics, the number of products in the drying chamber, and the volume of food being processed. SCADA (Supervisory Control and Data Acquisition) system software used to monitor and control industrial processes by recording real-time measurements of room parameters such as temperature, humidity, fan speed, and other environmental conditions, was used to control the meat block drying process. The developed forecasting model demonstrated high performance in forecasting the drying time (in hours) of meat products based on features obtained from ERP and SCADA systems. Using the XGBoost collaborative machine learning algorithm, the model achieved a high correlation of 0.96 between actual and forecast values. These results highlight the model's potential for practical application in the food industry, providing a reliable tool for resource optimization and improved production planning [110].

Using an expert system (ES), an information management system for the production of sausages of certain pre-determined quality has been adapted. This system takes into account potential nonlinear constraints on the quality characteristics of sausage products, or potential nonlinear criteria. The automated expert system for managing the technological process of meat and sausage production — the software package (SP) MultiMit Expert is based on two components: a database and a knowledge base, which enable the creation of an optimal recipe that meets consumer requirements. The ES has been tested for managing the production process and identifying defects in the recipe for Stolichnye boiled sausages with a high fat content. For example, the fatty pork content in the basic recipe was 32.65%; taking into account the recommendations of the developed expert system, the fatty pork content was adjusted to 27%. Thus, the recommendations of the developed expert system make it possible to improve the quality of the ready-to-eat meat product, increase the moisture-

holding capacity of the minced meat, which contributes to an increase in the yield of the finished product and an increase in the profitability of the meat product [111].

Using artificial intelligence and machine learning to improve the efficiency of cultured meat technology

CM) technology and assessed its future potential [112]. Optimizing cell lines for cell-based meat production is often challenging because it requires understanding the “state” of a cell or cell population (i.e., what genes and protein networks do) and selecting or engineering desired cell states. Measuring and forecasting these states involves interpreting complex interactions between genes and proteins, identifying those important for generating specific traits, and forecasting how perturbations will affect the overall process. Machine learning can be used to model these interactions using network analysis. In recent years, graph neural networks (GNNs) have been actively used to analyze biological networks [112].

Graph neural networks (GNNs) are another area of machine learning that works with graph-structured data and biological networks, such as protein interaction networks, gene co-expression networks, and metabolic networks [113]. GNNs have been implemented to forecast protein interactions [114], molecular interactions [115], metabolite-disease associations to understand disease causation [116], and others.

In addition, network analysis can help determine aroma and flavor [117]. Since meat aroma and flavor are largely controlled by metabolic pathways [118], network analysis can be applied in the biosynthesis of cultured meat to enhance aroma and flavor or add flavorings [112].

Technologies of RNA sequencing (RNA-seq) are commonly used to quantify cellular gene expression for cell line validation and optimization. However, analyzing RNA-seq or other omic data across many candidate cells is a complex and challenging analytical task. Machine learning can assist in this analysis in a variety of ways, including by grouping cells related to functionality using an unsupervised approach, gene expression profiling using a supervised approach, and identifying different types of tissue using unsupervised and semi-supervised approaches [112].

Using gene expression data to cluster cells based on cell type or behavior can help explain heterogeneity among cell populations and identify subpopulations with beneficial characteristics. When engineering cells for cultured meat production, scientists may want to isolate only certain cell types with optimal characteristics or remove undesirable cell types. For example, using single-cell RNA sequencing (scRNA-seq), Messmer et al. found that samples isolated from bovine muscle contain 11 different cell types [119]. Unsupervised machine learning can help map cellular heterogeneity by grouping cells related to functionality, identifying cell subpopulations, and performing dimensionality reduction. Typically, the input to an unsupervised

machine learning model is gene expression data obtained from RNA sequencing. In traditional machine learning frameworks that are not based on neural networks, the result is typically the assignment of a cluster number to each cell or to each gene [112].

Machine learning models have been successfully applied [112,120] in gene editing technology to identify regulatory areas that determine where, when, and how much a gene is expressed. The most relevant modern machine learning methods that have demonstrated their usefulness for solving these problems are generative adversarial networks, trained directly on genomic and transcriptomic data [121], and convolutional neural networks [112].

Microscopy is a fundamental technique in cell culture, providing information such as cell health (e.g., whether they are mitotic, senescent, or apoptotic); cell behavior (e.g., whether they are invasive, contractile, or secretory); and cell lineage (e.g., whether they are stem cells, progenitor cells, or terminally differentiated cells). The relevance of microscopy during large-scale production will particularly depend on its ability to serve as a low-cost, high-throughput tool. However, microscopy has historically been limited by the complexity of its analysis. Microscopic analysis is typically performed manually by researchers with well-trained vision, and its automated execution requires systems that can incorporate the many nuances of image data. Furthermore, the use of dyes to enhance image quality is undesirable due to cost and time constraints in the production of cultured meat (CM). For CM production, cell segmentation and classification are fundamental and indispensable due to their multifaceted contributions, including quality control, cell culture health monitoring, and production optimization. The use of machine learning approaches for automated cell segmentation and classification can reduce the time, costs, and errors associated with preparing for manual image data analysis [112].

Developing robust algorithms for cell detection and segmentation using computer vision requires access to large, diverse, and well-curated datasets with detailed annotations, and additional CM-specific datasets are needed to develop robust algorithms for accurate cell segmentation in microscopic images [112]. Much of the research interest has been directed toward deep neural network architectures, driven by convolutional networks for cell segmentation [122,123]. These architectures use encoder-decoder blocks to transfer features from multiple scales and levels to efficiently segment cells in histopathological and microscopic images. The U-Net model, a variant of the fully convolutional network architecture, has shown particular promise for this task. Unlike fully convolutional networks, U-Net incorporates skip connections that facilitate accurate semantic segmentation by fusing features from different resolutions, enhancing the model’s ability to capture complex details [112].

Transitioning CM cultivation from laboratory to industrial scale requires efficient bioprocess design. This involves using large bioreactors to create a controlled environment

for cell growth and differentiation that maximizes biomass and minimizes byproduct yield. The most straightforward application of machine learning to bioreactors is the use of machine learning-based models to manage bioreactor inputs. For monitoring and controlling bioreactors and industrial processes, wide range of machine learning models are used in bioprocesses, especially supervised learning models such as neural networks [124], random forests [125], and gradient boosting [126]. These learning methods do not necessarily require a prior understanding of the bioreactor biochemistry [112].

The sensory properties of CM, such as flavor and texture, are crucial to its commercial success. They can be obtained during cell culture from the flavor or textural components of cells, media, or scaffolds. Machine learning plays an important role in improving the analysis and identification of flavors and textures in other food products through the analysis of various types of data, and these methods will likely also play a role in the development of CM cultivation technologies. Recent research focuses on using the molecular structure and physicochemical properties of aroma compounds to forecast aromas, including taste or odor [127,128]. These characteristics are quantified as molecular descriptors — numeric representations that encapsulate the properties of the molecules involved. These descriptors then serve as input to machine learning models, which are trained to identify and predict flavor profiles and odor characteristics with greater objectivity. A wide range of traditional machine learning approaches can be used for this purpose, such as support vector machines, random forests, k-nearest neighbor, and AdaBoost trees [112,129]. In addition, deep learning approaches such as CNNs and multilayer perceptrons, and unsupervised learning approaches such as cluster analysis using principal component analysis, have been applied. Collectively, these methodologies have demonstrated that ML can make a significant contribution to improving the sensory properties of cultured meat and a range of food products [112].

Artificial intelligence for shelf life forecast

Accurate shelf life assessment is essential to ensure and maintain food safety, reduce waste and improve supply chain efficiency.

Traditionally, the shelf life of food products has been assessed using microbiological and chemical analysis, and sensory evaluation. Although these methods are effective, they are labor-intensive, time-consuming, and cannot fully account for dynamic environmental conditions, such as fluctuations in temperature, humidity, and microbial load during storage and transportation [130–132]. To address these issues, mathematical models have been introduced to forecast shelf life based on experimental data obtained using destructive or non-destructive analytical methods. The reliability of these models largely depends on the quality and accuracy of the analytical methods used to collect the data [132].

AI can be used to study data obtained from non-destructive testing methods such as hyperspectral imaging, spectroscopy, machine vision and electronic sensors to improve shelf life forecast [132].

The accuracy and reliability of artificial intelligence models for shelf life forecast depend significantly on the quality of the data obtained through analytical methods. Machine learning (ML) is a powerful tool capable of processing massive amounts of data, including food chemical composition, storage temperature, humidity, and non-destructive testing data, to accurately forecast product shelf life. Various traditional ML and new ML models have been developed and applied in the food industry. Traditional ML models typically require structured and manually developed features that are interpretable and struggle with high-dimensional and unstructured data. Deep learning technology, on the other hand, was developed to automatically learn feature representations from raw data using multiple layers of computation, which works exceptionally well with unstructured data such as images. The key difference lies in their complexity and feature extraction. While classical machine learning involves manual feature engineering, deep learning models are trained hierarchically from raw data and are therefore flexible but also computationally expensive. However, some of them have been used in forecasting the shelf life of food products [132].

Artificial intelligence is improving the accuracy of programs used to determine the shelf life of meat in food quality control. Current microbiological kinetic equations predict freshness under specific temperature conditions, but they become ineffective when the temperature fluctuates. To address this issue, deep learning methods were used to identify the internal relationships between temperature fluctuations during storage and a new CNN_LSTM (convolutional neural network with long short-term memory) model was proposed that predicts freshness parameters over a range of temperature fluctuations. Results showed that using the CNN_LSTM model yields more accurate forecast results than classical microbial kinetics methods such as the logistic equation, the Gompertz equation, and the Arrhenius equation, which are effective under fixed temperature conditions. Under temperature fluctuations, the model could still accurately predict the total viable cell count (TVC) under variable temperature conditions, with the coefficient of determination (R^2) exceeding 0.95 and the root mean square error (RMSE) less than 0.2. Furthermore, the model had the potential to forecast freshness under various changes in factors other than temperature fluctuations, which opened up new perspectives for forecasting produce freshness [133].

A number of researchers have developed machine learning algorithms to detect color, texture, and volatile organic compounds, as well as a range of other spoilage indicators, to assess meat quality in real time [132,134].

In a study by Italian scientists, various parts of chicken (breast, leg and thigh) were analyzed in terms of the content of ten biocompounds in the meat: nicotinamide, anserine,

carosine, malonic acid Dialdehyde and biogenic amines (putrescine, cadaverine, histamine, tyramine, spermidine, and spermine). The analysis was conducted on chilled chicken meat parts using three different packaging solutions: modified atmosphere packaging (MAP), vacuum packaging (SKIN), and packaging in O₂-permeable plastic film (STRETCH). The results showed that nicotinamide was the most discriminant compound, monitored for all chicken parts and reduced the research time. Notably, its concentration decreased over time, regardless of the packaging type. The cumulative contribution of all studied biocompounds to shelf life was identified using multivariate statistical analysis using partial least squares discriminant analysis (PLS-DA) and support vector machines (SVM). Both machine learning models demonstrated high classification accuracy: for different poultry parts, shelf life, and packaging used. The PLS-DA method achieved classification accuracies of 87 %, 85 %, and 70 %, respectively. SVM achieved higher accuracy rates of 97 %, 99 %, and 94 %, respectively. These results highlight the importance of considering the combined effects of all studied biological compounds. Furthermore, the obtained results underscore SVM efficiency as a discriminative multivariate approach to food classification [134].

Some key parameters used as chemical indicators in assessing quality and shelf life using digital technologies combined with machine learning (ML) include pH, water activity, lipid oxidation, and protein degradation. They have been regularly monitored to assess spoilage processes in various food products during storage and transportation [135]. Future research is expected to explore advanced data analysis approaches, such as deep learning, to facilitate the integration of spectral and spatial information in joint modeling.

The results of digital image processing technologies that detect color, texture, and changes in the appearance of products [132,135], combined with data from an electronic nose that detects volatile organic compounds released during spoilage [101,131], are transmitted into ML models that, by comparing these parameters with the rate of spoilage, predict shelf life in real time. The combination of digital technologies and machine learning forms a universal approach to quality management of a perishable product — meat [132].

The development of wireless sensor technologies (WST), which enable interconnection between the internet cloud and the physical world, based on smartphones with sensing and networking capabilities, has the potential to continuously monitor the temperature and humidity of meat storage in real time, inform consumers of the corresponding results, and further control the storage environment. The hardware requirements of a standard WST include: (1) a flexible wireless signal transceiver, (2) an energy-efficient microcontroller, (3) a long-life power supply, and (4) a high-performance sensor [136]. The revolution in information and communication technology has given rise

to many new applications, and many early applications have already been deployed in healthcare and logistics. In particular, several researchers have proposed smartphone-enabled wireless systems with wireless communication for meat quality monitoring to improve the fresh meat supply chain and ensure cost efficiency. Wireless/smartphone-based sensors for meat spoilage detection and quality control provide more reliable traceability throughout the supply chain. Instead of relying only on periodic inspections by government agencies and internal quality inspectors, manufacturers, distributors, and consumers can rely on these strategies to identify spoilage organisms and adjust storage environments to control food-borne hazards. Alternatively, this technology can be an effective method for obtaining expert opinions remotely, possibly even for further verification of relevant results [137].

One of the most important tools for ensuring meat safety is the use of various packaging solutions that extend shelf life and provide maximum convenience for consumers. Various types of packaging, including vacuum bags, aseptic containers, and modified eco-friendly packaging, are used in the food industry to extend shelf life, preserve freshness, and protect the food products from contamination [138].

Furthermore, AI-powered image analysis systems use image recognition and machine learning algorithms to thoroughly examine and authenticate packaging materials, labels, and codes on food products [139]. Their purpose is to ensure regulatory compliance and verify the accuracy of labeling information by identifying counterfeit packaging or labeling, ensuring consumer confidence. AI-powered machine vision systems play a significant role in improving product traceability, reducing the likelihood of inaccurate labeling, maintaining product quality, and enhancing consumer safety and satisfaction [140].

Automated systems with image recognition capabilities (AI Vision technologies) are used to confirm accurate packaging and labeling, thereby minimizing errors and ensuring compliance with regulatory standards [16]. Implementing AI Vision technology into packaging operations has the potential to transform the food sector by improving quality control, ensuring regulatory compliance, and providing consumers with quality products. Food companies are increasingly using personalized packaging to improve consumers' satisfaction and expand market covering [16].

Problems, challenges and limitations

AI and related technologies are creating a host of new complex interactions not only between humans and machines, between machines and machines [141], but also increasingly between machines and ecosystems, as well as with the Earth system as a whole. The introduction of AI and related technologies into the world of agriculture, agricultural processing, and resource management can be seen as adding new nodes and connections to these already complex socio-ecological and socio-technical systems [142].

There is growing interest and investment in the development and implementation of AI and related technologies in sectors critical to sustainable development, particularly the food industry. However, the efficiency of these technologies and the social, economic, and environmental impacts of their implementation unfold within a broader social, technological, and environmental context, making it difficult to forecast their implications in regards for distribution and sustainability [142].

In order to fully implement the potential of artificial intelligence and machine learning in the food industry, several obstacles must be overcome. The primary obstacle is the significant upfront financial investment required to implement these latest innovations. Purchasing and integrating advanced AI systems can be costly, especially for small and medium-sized businesses. Another major concern is the potential for cyberattacks and data breaches. Food industry businesses are more susceptible to cyberattacks that can steal sensitive data and cause operational disruptions as they become increasingly digitalized and networked. Reliable cybersecurity protection is essential to prevent such threats [16].

Although AI systems are often more accurate than traditional approaches, there are still challenges in maintaining their consistent performance and reducing false positives and negatives. Issues with scalability and compatibility with existing technologies and technical requirements can hinder the widespread use of AI technology [16]. For example, integrating AI technologies with existing food systems and processes can be challenging. Legacy systems may be incompatible with new AI solutions, leading to integration issues. Furthermore, ensuring the smooth operation of AI systems with existing hardware, software, and workflows requires careful planning and implementation. The application of AI requires transparency and interpretability of algorithms: many AI algorithms, especially deep learning models, are often considered “black boxes”, meaning their decision-making processes are not easily interpreted. This lack of transparency can be problematic in the field of food safety, where understanding the rationale behind AI decisions is critical to trusting the resulting data and ensuring compliance. Scaling AI solutions to handle large volumes of data and adapt to changing conditions can be challenging. As food safety needs evolve and data volumes increase, AI systems must be able to scale and adapt to new data types and scenarios [143].

Another drawback is that managing and operating AI-based systems requires a trained staff team. Despite the time and cost involved, investing in training employees to use the latest technologies is crucial. Addressing security and ethical dilemmas is also crucial. For example, using AI in the food industry to increase automation could lead to potential layoffs among production and management staff. To gain public trust and acceptance, AI systems must comply with security regulations and ethical principles.

While AI vision and machine learning have much to offer the food industry, their successful implementation and long-term sustainability depend on addressing issues such as cybersecurity risks, cost, accuracy, scalability, workforce skills, and ethical considerations [16].

When collecting and processing personal data, such as consumer reviews or health information, in food safety applications, privacy concerns may arise. The use of artificial intelligence and data analytics often involves collecting extensive data on individuals, which may include sensitive information. Mishandling or unauthorized access to this data can lead to privacy breaches and loss of consumers’ trust. Food safety systems often store and process large volumes of sensitive data, including supply chain information and quality control parameters. Leakage or loss of this data can compromise food safety, disrupt operations, and damage the organization’s reputation. Therefore, ensuring data security is crucial to preventing unauthorized access to information, data breaches, and cyberattacks [143].

The implementation of artificial intelligence and data collection technologies may have environmental consequences, such as increased energy consumption and growing volume of electronic waste. In the context of food safety, the use of complex sensors and computing resources may contribute to an increased overall environmental impact [144].

Conclusion

This article reviews the potential capabilities of artificial intelligence in the food industry, particularly in meat and poultry processing and livestock farming, and critically analyzes the challenges these technologies face and the innovative solutions they offer. The researches presented in the review shows that artificial intelligence possesses enormous potential for the digital transformation of the food industry, thus contributing to process improvement, higher product quality and safety, and more efficient resources management. At the same time, we also note the challenges associated with artificial intelligence, such as issues of data privacy and security, technical complexity and integration with classical (traditional) methods, as well as personnel qualifications. Using of artificial intelligence achieves technological, economic, and social benefits. The technological benefit is associated with: (1) increased accuracy and speed of production due to the human factor elimination; (2) reducing volume of rejection through automated quality control; (3) ensuring regulated food safety parameters (continuous monitoring of critical points). Economic effect — (1) reduction of operating costs due to reduction of manual labor, energy saving; (2) reduction of raw material losses due to optimization of ingredients use; (3) reduction of logistics costs (smart inventory management). Social effect — (1) product safety (control over storage and transportation conditions, prevention of food-borne diseases outbreaks); (2) creation of new professions (automation does not replace people, but transforms their role).

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