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RESEARCH ON THE INFLUENCE OF ARTIFICIAL INTELLIGENCE AND ITS SUBDOMAINS IN THE MEAT PROCESSING INDUSTRY

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Abstract

This study conducts a bibliometric analysis and narrative review of the impact of artificial intelligence (AI) on the meat industry from 2000 to 2023, using data from the Scopus and Web of Science databases. The results indicate a significant increase in AI research within the meat industry, with a particular emphasis on computer vision, machine learning, and deep learning. China and the USA are the leading contributors to this research, and keywords such as "meat," "quality," and "prediction" frequently appear in discussions. AI has been effectively applied in areas such as image processing, quality assurance, supply chain optimization, and predictive improvement. Emerging technologies like blockchain and computer vision have enhanced traceability and food safety. The analysis also highlights a growing interest in using machine learning and deep learning for meat deficiency detection, unauthorized activity monitoring. Although it offers numerous advantages, the integration of AI in the meat industry faces challenges, including data complexity, stringent regulations, high initial implementation costs, and the absence of standardized protocols, which limit interoperability. Successful integration of AI requires a balanced approach that combines human expertise with machine capabilities.

Key words: *meat, artificial intelligence, computer vision, machine learning, deep learning*

INTRODUCTION

Artificial Intelligence (AI) is an advanced technology that equips humans with software and tools to enhance learning, crisis handling, judgment, and innovation across various fields. The sustainability of a healthy economy requires among other things to assure food safety of the population. Based on the consumption dynamics, Machine Learning (ML) methods could provide useful tools in improving management along the food chain from agricultural farms to processing industry and final food in the consumers' plate.

In a word AI is an instrument which could help to predict statistics and making the right decisions at the national level [42, 43].

In the food industry in general, and in the meat processing industry in particular, automation entered relatively late compared to other industrial branches due to the raw materials that exhibit significant variations in terms of shape, texture, elasticity, etc. Additionally, there are hygienic requirements and physical factors such as high environmental humidity.

Currently, artificial intelligence has a significant impact on the meat industry, positively influencing the productivity of technological lines, process and inventory optimization, quality control of food products, and social aspects [20, 30]. The increased efficiency through AI implementation can be explained by replacing repetitive human activities, which in many situations occur at excessively high or low temperatures and very high air humidity [24]. In the supply chain, optimizing it with the help of AI can be achieved by improving stocks, waste reduction, and optimized distribution [20, 34]. On the other hand, cost reduction can be achieved by optimizing production and distribution processes, as well as improving resource efficiency, and this can be done based on market demand forecasting.[40].

In addition, especially in the meat industry, AI can be used to meet hygiene requirements in the field and ensure the quality of meat and meat products. Furthermore, it allows for efficient decision making, management of food waste, and the application of intelligent sorting and packaging solutions [26]. Additionally, AI can contribute to the development of new foods that strengthen immunity, evaluate diets, and predict the toxicity of food ingredients [27].

Alongside these advantages, there are social barriers that can be overcome through the financial and digital literacy development of farmers and the dissemination of best practices among participants in the food supply chain [6].

The goals pursued in this article are to examine and emphasize the progression of research in the application of AI within the meat industry over time, using two databases: the Web of Science (Clarivate) and Scopus (Elsevier) databases. The originality of this work consists in its comprehensive analysis of AI research in the meat industry. Both AI and its subfields, namely computer vision (CV), machine learning (ML), and deep learning (DL) represent the independent variables considered in the analysis, while the dependent variables include the dynamics of scientific research publications, the ranking of the top five most prolific countries, and the dynamics of keywords.

State-of-the-Art Review

In the pursuit of increased productivity in the meat industry, the adoption of new technologies has become a priority. Automation was first introduced in poultry and pork slaughterhouses [8]. However, the implementation of robotics presented challenges, as the items to be processed often lacked uniform shapes, sizes, and consistency [46]. After automating smaller and relatively uniform items, such as poultry carcasses or processing poultry meat for nuggets, the industry advanced to AI-based automation [7]. In this case, information about the entity is initially acquired using sensors, cameras, or other components; then, decisions are made using artificial intelligence, and finally, actions are taken [47].

The European Commission defines AI as systems exhibiting intelligent behaviour through the analysis of the environment and the execution of actions at various degrees of autonomy to achieve defined objectives. AI systems can exist either as software applications or as integrated components within hardware devices. For software, these systems function solely in the digital domain, such as in image processing (e.g., classifying beef or poultry carcasses). As for hardware integration, it involves advanced robotic systems [17].

Currently, AI encompasses the subsystem known as ML, which, in turn, includes DL [38]. CV plays a particularly important role in the meat industry by processing photos, videos, or 3D images, using DL models to identify or classify objects. [2].

At present, AI is utilized in the meat industry for:

• Robotics - AI-driven robots are employed in meat processing plants for tasks such as cutting, sorting, and packaging. They can work independently or alongside human operators to improve efficiency and reduce manual work [46].

• Monitoring – AI - equipped smart sensors can continuously monitor factors such as temperature, humidity, and other environmental conditions during meat processing. This helps maintain the freshness and quality of the meat [38].

• Quality control and inspection - CV technology can inspect meat products for defects, contamination, and ensure compliance with quality standards. This helps maintain consistency and enhance the overall quality of products [28].

• Traceability and Blockchain - Blockchain, integrated with AI, is utilized to ensure transparency and traceability within the meat supply chain. This allows for the provision of information regarding the origin, processing, and transportation of meat/animals. [10].

• Supply chain optimization - AI is employed to enhance and streamline the meat supply chain by anticipating demand, optimizing inventory management, and improving logistics. This helps reduce waste, cut costs, and ensure a more efficient distribution process [3].

• Predictive maintenance - AI algorithms are used for predictive maintenance of meat processing machines. By analysing data from sensors and equipment, artificial intelligence can predict when machines are likely to malfunction, enabling proactive maintenance and reducing downtime [23].

MATERIALS AND METHODS

Within this work, a semi-structured method is used, combining bibliometric analysis with narrative review.

Data Collection

To begin with, in the multidisciplinary databases Web of Science and SCOPUS, original articles, reviews, and books resulting from the search terms "meat" and "industry" or "processing" and "artificial intelligence" were identified. The chosen period ranged from 2000 to 2023. Since the number of articles resulting from the Web of Science database was lower when using the words "industry" or "processing" than in their absence, these were excluded from subsequent searches. On the other hand, since AI encompasses the subsystems mentioned earlier, namely CV, ML, and DL, it was considered necessary to collect literature separately in the two databases through the following three query variants: "meat" and "computer vision," then "meat" and "machine learning," and finally "meat" and "deep learning." This resulted in 8 datasets, 4 for each database. This allowed for a comparison of results obtained for the 4 research directions: AI, CV, ML, and DL, as well as a comparison of results between the two databases.

Data Analysis

For the analysis of the collected data, two AI-based chatbots were used. The data obtained from the Web of Science database were bibliometric analysed using the Biblioshiny tools from Bibliometrix package 3.1 in RStudio (version 4.1.2) [4,12]. Normally, this application allows the combination of data obtained from multiple databases.

Since the literature resulting from the Scopus database could not be exported completely due to recurring errors, these results were analysed using the analysis system provided by Scopus. The dependent variables analysed were those common to both bibliometric analysis packages, and the merging of analysis results was done manually. These common dependent variables included the temporal evolution of articles addressing the 4 subjects: AI, CV, ML, and DL, the countries from which the authors of these articles originated, and the temporal dynamics of keywords only for Web of Science. A narrative review was then conducted for these keywords.

RESULTS AND DISCUSSIONS

Establishment of Independent Variables

Table 1. Results obtained from querying the Web of Science and Scopus databases using three search variants

Search terms	Web of Science		SCOPUS	
	Total	Article type	Total	Article type
meat AND industry AND artificial AND intelligence	62	40 article 13 reviews 9 proceedings paper	3,712	1879 article 797 reviews 391 proceedings paper 325 books 286 books chapters other
meat AND processing AND artificial AND intelligence	86	51 article 14 reviews 21 proceedings paper	4,739	2593 article 920 reviews 599 proceedings paper 301 books 296 books chapters other
meat AND artificial AND intelligence	214	140 article 31 reviews 42 proceedings paper 1 capitol de carte	8,026	4630 article 1248 reviews 1119 proceedings paper 483 books 474 books chapters Other

Source: Biblioshiny, based on the WOS and Scopus dataset [48].

When using the search terms "meat and industry and artificial intelligence" in the Web of Science database, only 62 articles were obtained, while the combination "meat and processing and artificial intelligence" returned 86 articles. Much better results were obtained when using only "meat and artificial intelligence." Out of the 214 results, the majority were published in the journals: Food Science Technology, Computer Science Artificial Intelligence, and Agriculture Dairy Animal Science

As seen in Table 1 especially in the case of the Scopus database, the highest number of articles was obtained for the combination "meat and artificial intelligence." The main sources are Lecture Notes In Computer Science (including Subseries Lecture Notes In Artificial Intelligence And Lecture Notes In Bioinformatics), Foods, Computers And Electronics In Agriculture.

Dynamics of Scientific Research Publications

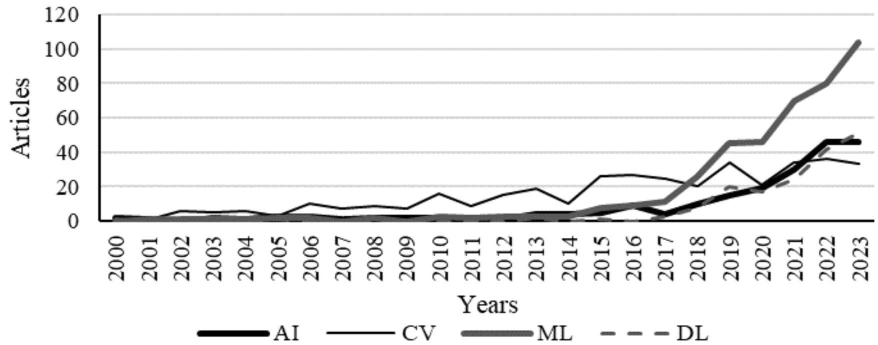
By excluding the terms "industry" or "processing" in the query, more results were obtained because there are numerous articles that focus, for example, only on meat quality, and these would not have been included in the results. For this reason, the search in the two databases continued using only the word "meat," to which the subdomains of artificial intelligence were added: CV, ML, DL. The temporal evolution of the four sets of queries in the two databases is presented in Fig. 1.

The temporal distribution of publications is presented in Fig. 1 and showing a significant increase starting from 2017. The maximum number is reached in 2022, with a slight decrease in 2023. Consequently, it can be stated that the topic is currently of significant interest.

As expected, more results were obtained by accessing the SCOPUS database.

In the first 2/3 of the studied interval, CV has the most articles due to concerns related to animal welfare and carcass classification.

Concurrently, with the increasing interest in ML and DL, the number of articles begins to rise, especially



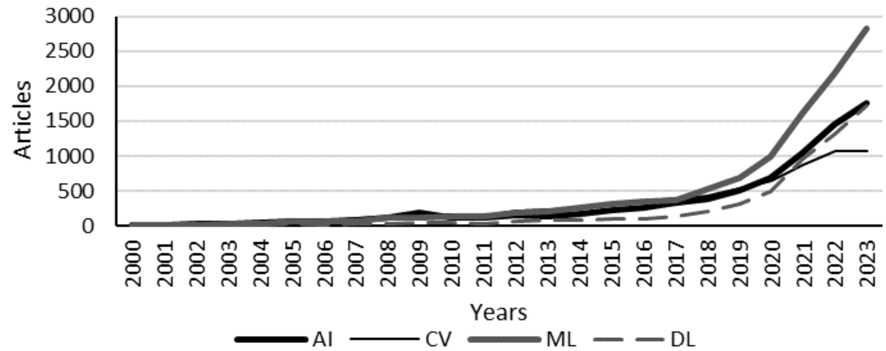


Fig.1. The dynamics of scientific research publications in the field of meat related to AI and its subsystems, as found in the Web of Science and Scopus databases

Source: Biblioshiny, based on the WOS and Scopus dataset [48].

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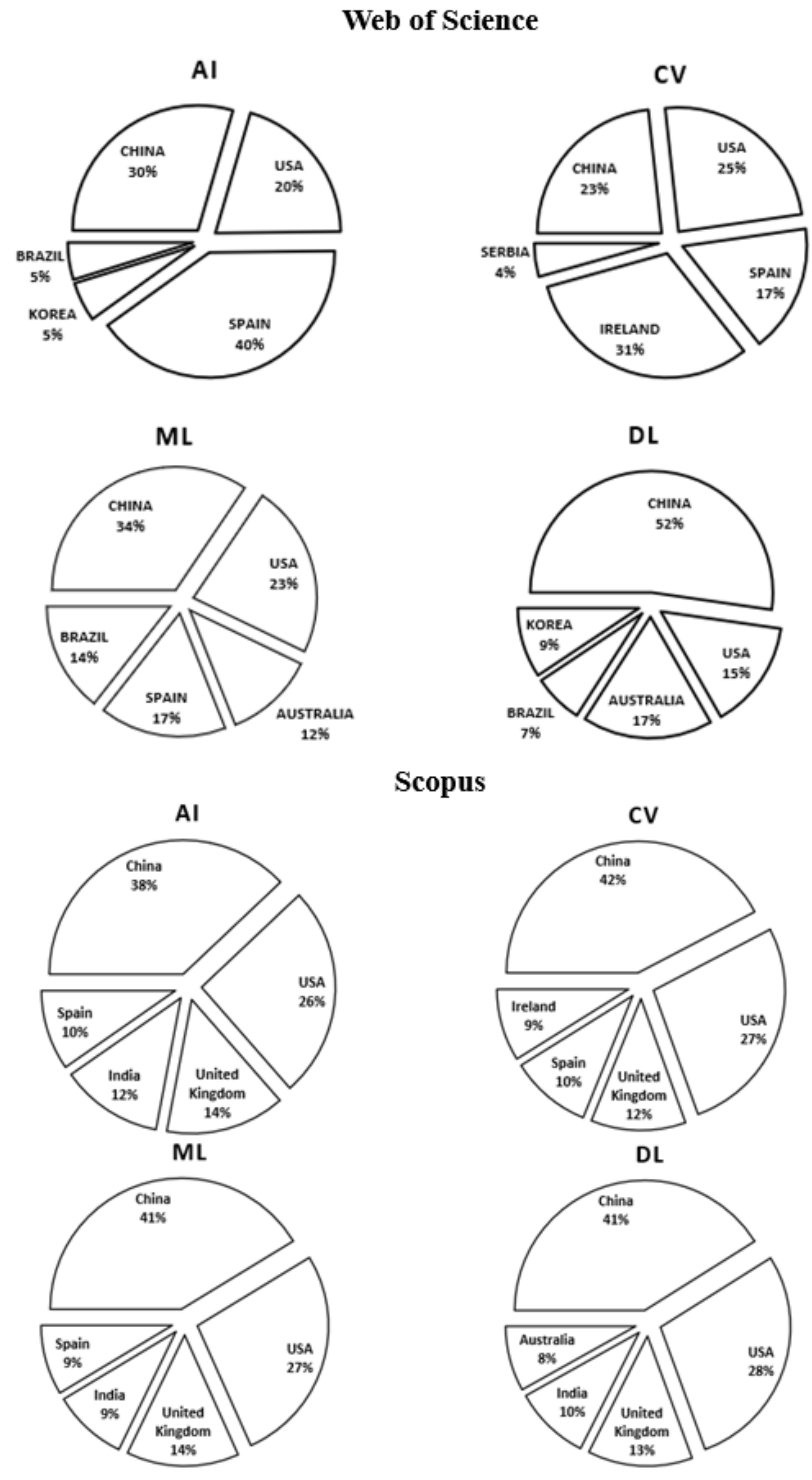

Fig.2. Proportion of the top five countries contributing to scientific research in the field of meat industry related to AI and its subdomains, present in both databases
Source: Biblioshiny, based on the WOS and Scopus dataset.

	AI										CV									
Year	MEAT	QUALITY	PREDICTION	CLASSIFICATION	SYSTEM	COMPUTER VISION	SPECTROSCOPY	SYSTEMS	BEEF	GROWTH	COMPUTER VISION	PREDICTION	QUALITY	MEAT	CLASSIFICATION	COLOR	QUALITY EVALUATION	BEEF	MEAT QUALITY	SYSTEM
2001	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2002	0	0	0	0	1	0	0	0	0	0	0	1	1	0	1	1	0	0	0	0
2003	0	0	0	0	2	0	0	0	0	0	0	1	1	0	2	1	0	0	0	1
2004	0	0	0	0	2	0	0	0	0	0	0	1	1	1	4	1	0	1	0	2
2005	0	0	0	0	2	0	0	0	0	0	0	1	2	3	5	2	0	1	0	3
2006	0	0	0	1	2	0	0	0	0	0	4	3	5	5	11	2	1	6	5	4
2007	0	0	0	1	2	0	0	0	0	0	7	5	6	7	12	2	1	7	6	6
2008	0	0	1	1	3	0	0	0	0	0	13	6	7	8	14	5	1	9	9	8
2009	1	1	1	1	3	0	0	0	0	0	15	9	8	10	15	8	1	9	12	8
2010	1	1	1	1	3	0	0	0	0	0	19	13	11	15	17	11	2	12	14	10
2011	1	1	1	1	3	0	0	0	0	0	21	15	12	15	17	12	3	12	15	11
2012	1	1	2	2	3	0	0	0	0	0	25	19	16	16	20	15	5	13	16	11
2013	2	1	2	2	3	0	0	0	0	0	34	23	19	22	22	18	12	17	17	13
2014	2	2	2	2	3	0	0	0	1	1	35	26	23	23	23	21	12	18	19	13
2015	2	2	2	2	4	0	0	0	2	2	48	33	31	28	27	24	20	25	20	14
2016	3	2	2	2	4	0	1	0	2	2	63	42	34	30	33	30	27	28	24	15
2017	3	2	2	2	4	0	1	0	2	2	78	43	39	35	35	34	32	28	26	15
2018	4	3	3	4	4	0	2	0	3	2	85	47	40	41	42	38	35	29	31	19
2019	5	4	4	7	4	0	3	1	4	2	92	56	50	44	46	41	38	32	32	20
2020	6	5	5	8	4	0	3	1	4	5	99	60	52	49	51	43	38	34	33	21
2021	11	5	7	9	6	1	5	2	4	6	106	63	58	52	57	51	41	34	37	26
2022	17	10	11	10	8	3	7	5	5	7	114	69	66	58	59	51	42	39	37	32
2023	25	17	14	12	9	8	8	8	6	7	125	73	72	63	61	53	42	41	38	37

	ML										DL									
Year	MEAT	QUALITY	CLASSIFICATION	PREDICTION	IDENTIFICATION	SPECTROSCOPY	BEEF	SYSTEM	REGRESSION	PORK	MEAT	QUALITY	CLASSIFICATION	PREDICTION	BEEF	MODEL	SYSTEM	BEHAVIOR	COMPUTER VISION	MEAT QUALITY
2001	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0
2002	0	0	0	0	1	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0
2003	0	0	0	0	1	0	0	2	1	0	0	0	0	0	0	0	0	0	0	0
2004	1	0	0	0	2	0	0	2	1	0	0	0	0	0	0	0	0	0	0	0
2005	2	0	0	0	2	0	0	2	1	1	0	0	0	0	0	0	0	0	0	0
2006	2	0	1	0	2	0	0	2	1	1	0	0	0	0	0	0	0	0	0	0
2007	2	0	1	0	2	0	0	2	1	1	0	0	0	0	0	0	0	0	0	0
2008	2	1	1	0	2	0	0	2	1	1	0	0	0	0	0	0	0	0	0	0
2009	2	1	1	0	2	0	0	2	1	1	0	0	0	0	0	0	0	0	0	0
2010	3	2	1	0	3	1	0	2	1	1	0	0	0	0	0	0	0	0	0	0
2011	3	2	1	1	3	2	0	2	1	1	0	0	0	0	0	0	0	0	0	0
2012	3	2	2	2	3	2	0	2	1	1	0	0	0	0	0	0	0	0	0	0
2013	3	3	2	2	3	3	1	2	1	1	0	1	0	0	0	0	0	0	0	0
2014	3	3	2	2	4	3	1	2	1	1	0	1	0	0	0	0	0	0	0	0
2015	4	4	3	2	4	3	2	3	2	1	0	1	0	0	0	0	0	0	0	0
2016	7	8	5	3	5	4	3	3	3	2	0	1	0	0	0	0	0	0	0	0
2017	7	10	5	6	5	4	6	4	3	4	0	1	0	1	0	0	0	0	0	0
2018	10	15	9	11	8	10	10	5	3	8	2	3	2	2	1	0	0	0	0	0
2019	14	22	17	14	12	13	12	7	6	11	6	6	5	4	4	1	0	1	2	0
2020	23	27	27	19	17	18	15	9	10	12	7	7	9	5	6	2	0	1	3	2
2021	36	35	39	28	21	22	17	12	12	14	13	11	12	7	6	4	3	2	5	3
2022	58	45	45	35	31	24	22	15	15	15	19	15	15	10	8	8	6	6	5	3
2023	81	64	56	43	35	29	25	23	23	18	28	23	19	14	10	10	9	8	8	8

Fig.3. Dynamics of the top 10 keywords in the Web of Science database
Source: Biblioshiny, based on the WOS and Scopus dataset [48].

Ranking of the Top Five Most Prolific Countries

The top five countries presenting the results of their research in the field of AI and its subsystems are shown in Fig. 2. In all datasets, China is followed by the USA, except in Web of Science research related to CV, where their positions are reversed. Generally, China holds the first place, but in the case of AI and CV within Web of Science, it ranks 2nd and 3rd, with Spain and Ireland, respectively, and the USA taking the lead. On the other hand, Spain appears in these rankings except for DL in both databases.

Fig. 2 also reveals that the United Kingdom and India are only present in the Scopus database, while Brazil and Korea appear in Web of Science.

Dynamics of Keywords

The trend in keyword usage in Web of Science-indexed research is presented in Fig. 3. As expected, in all four sets, the most frequently appearing word is "meat," followed by the word "quality," except for the CV-related set. Among the cattle species, beef and bovine meat were the most studied. There were numerous attempts, especially for cattle, to classify carcasses using artificial intelligence, particularly since the price is determined based on the quality class [15]. Classification is also used in assessing meat quality [33].

Another frequently appearing word is "prediction" regardless of the chosen independent variable. Using AI algorithms, historical data can be analysed to predict future demands, reduce unplanned downtime, optimize resources, etc. [32].

Narrative Analysis of Keywords

AI along with its subsystems has been introduced into the meat industry to achieve one of its major objectives, namely the quality of products [24].

For example, image processing and ML models provide non-invasive opportunities for food safety and inspection in meat industry units with large production capacities [14]. In this regard, the detection of pork chop quality based on its colour and marbling can be mentioned [39]. Using statistics and AI, the freshness of salmon can be determined based on eye colour [22], or the freshness of beef, and the required equipment being portable can be positioned where desired [5]. Another issue that can be addressed in this way is the detection of meat exhibiting abnormal states, especially PSE, which poses significant technological challenges [13].

DL has been used to highlight frauds such as the substitution of minced beef [36].

ML models are employed to train the CV system to recognize and classify various types of defects in meat products. These models learn from a large set of labelled image data to accurately identify and classify defects, such as discoloration, bruises, and foreign objects [21]. In various cases where CV is coupled with AI, data acquisition is practically done using video images, ultrasound, nuclear magnetic resonance, computed tomography, dual-energy X-ray absorption, near-infrared spectroscopy, and hyperspectral imaging. Essentially, image recognition algorithms in AI-based computer vision technology operate through: 1-image pre-processing using spatial domain and transformation domain methods; 2-image segmentation by selecting illumination, image filtering, and thresholding; 3-extraction of features such as size, shape, colour, and texture for subsequent analysis and classification; 4-defect classification based on the extracted features, generally using artificial neural networks, decision trees, fuzzy logic, and support vector machines [16].

Therefore, a key benefit of AI lies in maintaining food safety and quality by ensuring compliance with safety standards and preventing cross-contamination with foodborne pathogens [3]. The use of computer vision in meat processing can lead to waste reduction by providing rapid, accurate, and non-destructive detection methods for meat quality assessment [37].

Another important aspect is optimizing the recipes of meat products in terms of taste and nutritional value. In this case, the challenge lies in the creativity and practical nature of recipes generated by AI. These can be quickly generated, allowing for the discovery of new flavour combinations and personalized recommendations [44].

Traceability involved in food safety can be enhanced with the help of AI by finding solutions such as Boxed Meat Label Verification (BLV) systems, which verify the type of meat compared to the label data [21]. Additionally, artificial intelligence can be used in conjunction with other technologies such as cloud computing and the Internet of Things to create personalized traceability systems [11].

Predictive artificial intelligence is used in the meat industry to enhance various aspects of production, processing, and supply chain management.

Wang *et al.* (2021) developed a framework for weight estimation and prediction to support intelligent production decisions, thereby increasing poultry slaughter yield and, consequently, revenue [45]. Technologically, artificial intelligence predictive modelling has been employed for pork colour and marbling degree, processing line speed, with prediction result accuracies of 92.5% and 75.0%, respectively [37]. From these examples, it can be stated that predictive AI allows the automation and optimization of meat processing, leading to increased productivity and unit efficiency [9]. On the other hand, predictive AI can enhance the meat industry's supply chain by optimizing logistics, food delivery, and predicting maintenance in food processing machinery. It can also help reduce food waste and contribute to sustainable consumption by decreasing the carbon footprint of food [34, 3].

However, there are challenges in using AI algorithms, such as predicting future demand for certain meat products. In this case, a challenge is the variability of internal and external factors that can affect demand, such as promotional offers, seasons, and holidays [29]. Another challenge is the complexity and diversity of data in the food industry, requiring the development of machine learning models specifically tailored to the industry [32]. Additionally, accurate demand estimation is crucial for perishable food products, as excess stocks can lead to food waste and monetary losses [19].

Furthermore, in some cases, obtaining accurate and sufficient data for training AI models can be a challenge. If the data is incomplete, biased, or not representative, it can affect the performance and reliability of the AI system. Also, data transfer through various networks makes them susceptible to cybersecurity threats [18].

On the other hand, as previously mentioned, meat processing involves a complex set of tasks, and the variability of raw materials can be significant [41].

The meat industry is subject to strict regulations and standards for food safety and quality, meaning the implementation of AI technologies may require compliance with additional regulations compared to other domains. This is compounded by the absence of protocols and standards for AI applications in meat processing, which can hinder interoperability and collaboration between different systems [31].

Due to significant initial costs, including hardware acquisition, software, and staff training, implementing AI systems in medium or small-capacity processing units is challenging. This is coupled with expenses for monitoring, continuous updating, and maintenance [1].

Integrating AI systems into existing meat processing workflows requires careful consideration of human-machine collaboration. Ensuring that AI technologies complement human abilities and work seamlessly with human operators is essential for successful implementation [35].

Some AI algorithms, especially deep learning models, may be perceived as "black boxes" because their decision-making processes are not easily explainable. In industries with strict regulatory requirements, such as meat processing, the lack of transparency in AI decision-making can pose challenges [25].

CONCLUSIONS

This study aims to analyse research published between 2000 and 2023, using the Web of Science and Scopus databases, regarding the impact of AI and its subdomains: CV, ML, and DL in the meat industry. Through bibliometric analysis, an increasing interest has been observed, especially in the last six years, regarding the progress brought about by the implementation of AI, CV, ML, and DL. The main countries contributing to the specialized literature in this field are China and the USA, along with European countries such as Spain, Ireland, and the United Kingdom.

The keyword analysis revealed that research concerns are primarily focused on "quality," "bovine" meat, and "prediction," indicating a major focus on ensuring product quality and process optimization. In the narrative analysis of these topics, the benefits of AI and its subdomains were highlighted, along with the challenges and respective limitations. Thus, it was shown that the use of AI algorithms faces difficulties such as variability in factors affecting demand, data complexity in the industry, and strict regulations for food safety. Possible errors and, not least, significant initial costs were also identified.

On the other hand, while AI can replace repetitive work in unfavourable environmental conditions, the integration of AI systems requires careful human-machine collaboration.

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