Applications and Business Impact of Artificial Intelligence in the Industrial Production of Food and Beverages

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Abstract The food and beverages industry is required to adapt to an increasingly complex and constantly changing environment and market. Digital technologies, in general, and artificial intelligence, in particular, can play a key role in helping firms in this industry face this challenge and in boosting the quality and safety of their products. This article identifies the main problems arising from the capillarization of digital technologies in society as well as some solutions and methods being used today to guarantee product quality and safety. In view of the limitations of these methods and solutions and to face the changing paradigm for quality and safety in the production of food and beverages, this article describes different experiences in the application of artificial intelligence techniques in various fields, and their impact in business terms for the industry. Finally, the article mentions the main challenges in the application of these technologies in order to make progress beyond the state of the art.

1 Introduction

Today the agrifood sector faces numerous challenges that make it necessary to change many practices and processes in the production and sale of its products, among others: growing market pressure resulting from globalization and increased competition; the need for increasingly differentiated and segmented production; complex requirements for quality assurance; legislative changes requiring more intense processes for quality control and improvement; food safety and traceability requirements throughout the production chain; the need for more reliable and flexible product provision; the need for a better understanding of consumer behavior and trends; and the adoption of sustainable practices.

One of the above-mentioned challenges for the industry stems precisely from progress made in digital technologies, and their extension and capillarization.

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While such technologies have become cheaper and knowledge is now available on how to develop and adopt them, there has been a radical change in people's eating habits. The market has changed, and new consumers are much more demanding and aware. They have more information to help them decide and are very concerned about what they eat and their way of life. Their needs are increasingly personalized, and they interact with other consumers via various channels. This has led to completely new approach strategies for the organizations that aim to satisfy such new consumers.

Nevertheless, digital technologies have not only changed the way in which consumers reach decisions. They have also changed the structure of the competitive fabric. Such technologies are breaking the rules regarding who has access to interfaces with the market and with market operators, since the digital environment enables producers and consumers to have a direct relationship.

Such changes are, therefore, leading to a transition towards a new model of competition, oriented to the "servitization" or "product as a service". Consumers are increasingly consuming 'services' rather than products, that is, they expect the food products they purchase to add to their quality of life in hedonistic or functional terms. All this is also shaping a new model of collaboration in the value chain and a new productive model. Placing a product on a supermarket shelf is no longer up to a single organization but is determined by a set of them working in, not only on a chain basis but also on a network basis and in a coordinated and synchronized manner to respond fast and effectively to constant changes in preferences and trends. Innovation (in both process and product) has to be increasingly fast and constant. More flexible production mechanisms are needed to orient production not to bulk volumes but to small, even sometimes customized amounts. This requires setting up a production model that is conceived more as ingredient 'assembly' than as a traditional mass production. This is made possible by strong connectivity among the elements involved in production: people, machinery, information systems, and processes that must work in a coordinated way, generating a large amount of information about the production process so that fast decisions can be taken.

This change of paradigm, which is much more complex and dynamic than ever, amounts to a huge challenge for efficiently guaranteeing product quality and safety. Added to this, other aspects such as wide product heterogeneity and the specific nature of perishable products, are also highly relevant. These factors create a further challenge for managing product quality and safety, a problem that is less relevant in other sectors in which production is more homogeneous in terms of product variety.

2 Identification of Sector

The European agrifood industry is made up of a total of 291.000 firms (data for 2020) (FoodDrinkEurope, 2020) and employs 4.82 million workers, which amounts to 15% of all industrial employment. It is the leading industrial sector in terms of volume, added value, and employment. According to figures for 2020 (FoodDrinkEurope), its sales were valued at 1.2 billion euros. The sector is characterized by the great variety of its activities and, consequently, of structures and production methods, as well as great fragmentation, with small and medium enterprises predominating. The European industrial sector, of which the food industry takes part, includes about 2 million firms employing approximately 35 million people and representing 20% of employment in the EU. In spite of these large figures, according to the European Parliament (2015), the European economy has lost one third of its industrial base over the last 40 years and has lost added value. This fact is key for explaining any action in the sector as well as the priorities of firms working in it.

The agrifood industry is heterogeneous and includes firms with a wide range of products of different types although some sectors contribute more than others, such as the meat sector, which represents about 20% of the industry, beverages with about 15%, and dairy about 14%.

The industry also has certain specific characteristics that set it apart from others:

– Its products have to be produced and distributed in safe conditions without pathogenic microorganisms (Mortimore, 2000). This is especially the case for fresh and refrigerated products because poor management of such aspects may result in a public health problem for consumers.
– Its products are perishable (Holley & Patel, 2005), to a greater or lesser extent depending on their specific characteristics and the processes they undergo. It is therefore necessary to monitor their shelf-life both when it is short, as with fresh products, or when it is long as with products that are cured or subject to thermal processes to eliminate micro-organisms or for the purpose of sterilizing their packaging, etc.
– Regulation is very strict in terms of product classification in categories, consumer information and labeling, traceability and product safety control, with different levels of stringency in different markets and with supervisory bodies such as the FDA (Food & Drug Administration, 2021) in the United States or EFSA in Europe, as well as those of each EU member country (European Union, 2021).
– The food production industry is a processing industry. It entails a chain of processes for transformation, addition of ingredients, and processing of a set of raw materials, sometimes also involving microorganisms for biological processes (such as fermentation) or chemical reactions and physical processes arising during production or during the shelf-life of the product until it is consumed.
– Consumers exert a great influence on patterns of consumption and on the demand for certain products and have high visibility on social networks. This forces firms to undertake constant innovation in types of product, processes, formats, and distribution channels, among other areas.

In addition to all the above, food is essential for human life. It is directly related to human health in terms of both availability and its direct effect on people's health when ingested. Moreover, it has to be made available for purchase, whether fresh or processed and whether it has a long or short shelf-life. This requires extensive infrastructure allowing for distribution with great capillarity to all the places where consumers can acquire the products. Food is closely related to peoples' culture and identity and, in some economically more developed societies, it may also take on great importance in a hedonistic lifestyle.

These are the main characteristics of the industrial food and beverage sector. They must be taken into account in the design of any technology if it is to be effective in the sector. Moreover, each sub-sector, such as meat or dairy, may have different needs and product types that set it apart, not to mention the many agents and factors involved in the production, distribution, sale, and consumption of a food product.

3 Problem Statement

The physical, chemical, and microbiological (even organoleptic) characteristics of each type of product (meat, dairy, etc.) vary depending on the food type and change during processing throughout the chain of production. A food is a dynamic system of behavior that varies over time, and there are a multitude of causes for such variations (seasonal/climatic, geographical, species, breed, variety, sex, handling, feed, etc.). Shelf-life or expiration date depends on many factors. Standardizing conditions for production and distribution aims to reduce such variability and to offer products with uniform quality. However, there is an intrinsic variation between batches produced in the same conditions. Processed foods have a diverse final composition which depends on the combination of raw materials, amounting to a complex matrix. Each constituent element has its own behavior and properties and requires specific analytical techniques. Moreover, if quality characteristics are to be analyzed and managed, they must be translated into mathematical language; a specific characteristic (such as weight, color, tenderness) must be expressed numerically so that a population/batch/sample can be described in statistical terms (distribution, mean values, and deviations). From a mathematical point of view, product quality can be said to remain constant as long as the statistical distribution of its quality characteristics does not change.

Certain sensory attributes are subjective and are therefore assessed by tasting panels. Special care must be taken in the selection and training of such panels, the drafting of tasting sheets, the methodology used, and the statistical analysis of the information obtained. Some quality attributes ("experience attributes") can be assessed by the consumer only on purchase or consumption, while others require analysis by specialists rather than consumers ("belief attributes"). To resolve this problem, the latter are presented to the consumer by means of information printed on the label with, for example, quality labels that certify that the producer complies with certain quality standards.

Therefore, the sector has to develop new strategies in order to guarantee safe, quality products in an efficient and sustainable way at the point of sale, in an increasingly complex environment. It is in this context that new advances in artificial intelligence have an essential role to play.

4 Description of Previous Solutions

Artificial intelligence (AI), a discipline that solves problems using a variety of computational techniques, is becoming hugely relevant. Over the last decade, according to the experience of the authors, most of the advances in AI in the food sector have focused on developing models and simulating problems in the behavior of food matrices or of products from the point of view of food safety, always in a laboratory environment and under very controlled conditions. Authors are now observing an explosion in technological proposals and even new applications, in addition to those already mentioned, such as market research and consumption, and analysis of texts in digital publications.

However, today most AI technologies in the agrifood sector are being used in the following 3 main areas:

- Quality control in food production
- Production of food that is safe for consumption
- Compilation of textual information on the market and the sector using natural language processing techniques.

Other areas of action, such as precision agriculture and business analytics, use specific AI techniques for analyzing datasets from the agricultural production environment and from business indicators (sales, customers, market segmentation, etc.), but these fall outside the scope of this article.

The following section covers some of the current solutions adopted in each of the main areas mentioned above, as well as the limitations that are driving the development of new AI-based solutions.

4.1 Limitations of Current Solutions for Quality Control in Food Production

For the agrifood industry, it is important to define the quality attributes that are most highly valued by consumers, as well as their relative importance and how they are assessed. A food is considered of good quality when it meets consumers' needs, which in Europe are food safety, nutritional quality, and healthiness (in the diet as a whole), desirable organoleptic characteristics, and other attributes (environment-friendliness, sustainable development, transparency, and information).

After defining these, a firm's main concern is to achieve continuous production and supply of a product with constantly improving quality. The food industry has drawn up regulations and systems to control and manage quality, including Hazard Analysis and Critical Control Points (HACCP) and Good Manufacturing Practices (GMP). It has also adapted models initially developed for other industrial sectors (ISO standards). The ISO and HACCP systems are preventive and, since monitoring is reported in a set of documents, audits can be carried out and industries standardized.

The HACCP system essentially manages health risks, while ISO standards cover all aspects of quality. There is already a specific regulation (ISO 22000:2005) that lays down requirements and allows for the operation and maintenance of general food safety management systems in the industry.

The HACCP system is used to identify and assess risks, and to monitor in any production process the key points that might affect the safety of a food. There are also regulations set up by large retail chains applying their own safety and quality parameters, such as Global GAP, British Retail Consortium Standard, UNE 155,000, IFS (International Food Standard), and SQF (Safe Quality Food).

Quality control within the industry may not guarantee the safety of the end product because it might be exposed to external changes. For example, for chilled products, it is essential to maintain the cold chain at all times to preserve microbiological stability. This reinforces the fact that distribution and transport operations are an essential part of the agrifood industry and have an impact on product quality and safety.

Quality control in food production may adopt different approaches because of the wide variety of products and of situations. From the point of view of the processing received by products and the raw materials used to make them, products can be grouped as follows:

- Group I (Fresh produce): This group covers fresh foods in their natural state such as fruit, vegetables, meat, fish, and eggs as well as other foods preserved using traditional methods (salting, dehydrating, etc.). Such foods have not been processed and have not undergone any preservation treatment so are very perishable (short shelf-life) and often need refrigeration to prolong their shelf-life.
- Group II: canned or semi-conserved products such as tuna in (oil, mayonnaise, jams), which are usually subject to thermal treatments to sterilize the product and prolong preservation. Usually presented in sealed containers (cans or glass jars).
- Group III: food preserved by freezing or deep-freezing such as fish, vegetables, shellfish, and meat. Defrosting is necessary before consumption.
- Group IV (pre-prepared convenience food): foods such as vegetables, fresh fruit (e.g. sliced mushrooms, cut fruit that is first selected, washed and vacuum-packed or packed in a controlled atmosphere), for which the cold chain must remain unbroken during distribution.
- Group V (pre-cooked convenience food): ready-to eat foods, mainly dishes made up of many ingredients and subject to complex production processes, including thermal processing and packaging in addition to chilling for preservation after packaging.

Different aspects of food safety are stressed depending on the group in which the food is classified. For example, for some foods the emphasis is on evolution of the product's shelf-life and on microbiological control in production conditions (as in a microbiological fermentation process); for others it is on control of the physical and chemical, and even microbiological evolution of the product quality as perceived by the consumer throughout its shelf-life (as in the control of micro-organisms that might affect quality). For other groups or even for types of product within a given group, it may be much more important to analyze the impact of the productions conditions on the product or to understand the influence of the origin of raw materials, or of the packaging, or many other factors.

Whatever the group, in the food sector there are various software applications for quality control, some of which are specific to the food sector while others are more widely used but can be adapted to the characteristics of different types of product. All of which offer basic functionalities such as:

(a) oversight and reports on Control Points
(b) document management
(c) human resources management
(d) management of suppliers and customers
(e) management of audits and non-conforming products
(f) management of equipment maintenance
(g) product traceability
(h) alerts management.

Where laboratory analysis exists, this is usually limited to the checking of certain balanced scorecards as a statistical summary of the main elements of the system. Some of the solutions are connected with production control systems of the MES/MOM type and can draw up graphs of production parameters and alert when pre-set thresholds are passed.

Many firms use ad-hoc solutions to monitor certain quality indicators and HACCP and for real-time production control. However, these do not usually have advanced analytical capability and do not allow product quality control to be connected with the pre-set production conditions and contexts. The basis for analysis is good data collection, and software should have specialized analytical capability and be available for any situations arising.

Another important matter for the food industry is to know in detail how certain key processes perform. For example, software-based simulation mechanisms may be very useful in processes that analyze in detail a given single process in order to find how it really affects the product (as in an emulsion with a fat such as oil, as is often used in sauces).

In the food sector, process simulation (Pieter Verboven et al., 2020) has not evolved as fast or as much as in other sectors, such as pharmaceuticals or chemicals, and still has many shortcomings. One reason for this is that each firm usually devotes resources to research and development precisely because it seeks a unique, differentiated product. This means that processes are very elaborated and streamlined to give a specific organoleptic response in the product or to focus on physical parameters such as size, texture, resistance to pressure, color, and freshness.

There are software applications for the simulation of industrial processes, which simulate chemical reactions, mass transfer processes such as drying for meat or hydration processes, or thermal processes such as those that eliminate pathogens. There are also solutions of generalist simulation software (widely used to simulate multi-parameter physical processes), open source and that can be integrated with third-party software, or other suites, which are widely used in the industry for a variety of physical phenomena. These can give good simulation results provided that the conditions adapt well to the system of equations to be modeled and to the physical and chemical phenomena involved. On a microbiological level, there are modeling suites software platforms, which are available for the product families that are most prone to the micro-biological development of pathogens or to spoilage. Such models describe very well the growth of micro-organisms in controlled conditions but not in a dynamic environment such as production. So, as the production industry in general over the last 10 years and the food industry in particular more recently have gradually adopted computing capability as a result of the availability of data in digital format (Sartal et al., 2019). These are widely used in very intensive, efficient industries such as the automotive or fast-fashion sector, with well-known techniques such as 6-Sigma and agile (Sartal et al., 2017). In the food industry, however, they are being adopted more slowly.

So there are currently no market solutions for process modeling that can be directly and easily adopted to simulate and explore what happens to product characteristics in the food processing industry, in which process interaction is very dynamic.

4.2 Limitations of Prior Solutions for the Management of Food Safety

Among commercial information systems for food safety management, those with the most complete functionalities aim to support HACCP processes. This is a set of procedures to control certain parameters, especially in production lines so that, if certain limits are exceeded (e.g., a product has not remained long enough in a thermal process), alarms are tripped so that users can make any necessary corrections and avoid subsequent risks for the product.

In all of them, control is from the point of view of HACCP, that is, it is reactive. They can connect with probes, sensors, and the information systems of the production system and generate alerts that figure within the actual HACCP plan. However, there is a clear opportunity for progressing in the advanced treatment of the data and for linking the process variables they monitor with the microbiological state of the product. This can add analytical capability to the service provided by the organization's experts, generating a link between the process and food safety.

When updating their systems, firms often introduce software and hardware (probes) or autonomous systems that can emit alerts in the case of changes or trends in a limited number of key variables that are present in their HACCP plan. In all cases, firms either adopt ad-hoc solutions developed by their own IT teams or use generalist solutions.

However, if the problem requires finding out more about what happens in the control of microbiological risks in order to simulate to a greater degree what might happen in the short term on a specific line or a part of it, then a distinction must be made between two large families of mathematical models for assessing microbiological risks in the agrifood context from the predictive point of view:

– Mechanistic models based on equations, also known as white box models.
– Machine learning (ML) models, that is, "black box" models, based on data compiled from the variables that describe the phenomenon.

This type of distinction also applies to the simulation and profound knowledge of the impact of the process conditions on the above-mentioned quality variables.

Various software solutions using mechanistic models are available, both open and commercial. This type of predictive microbiology model is useful to reveal the behavior of microorganisms (presence, trend of populations over time, etc.) in certain food matrices under static conditions, that is, under controlled temperature, humidity, pH, etc. They provide key information on optimal conditions for the growth and presence of such microorganisms as well as on the factors that eliminate them. However, such models cannot be extrapolated to a production environment in which conditions are dynamic. Also, there is interaction between the various processes taking place in the production plant, including not only the production processes themselves but also hygiene patterns, company culture, etc. Moreover, in most cases, the microorganism to be modeled has to be inoculated in the actual food matrix. This cannot be replicated in a real production context because of the effects it might have on subsequent production.

4.3 Limitations for Collecting and Processing Textual Information on the Market and the Sector

There are many social media analysis services available in national and international contexts that can measure, filter, and process publications and perform brand, reputation, and sentiment monitoring. Many of them include mechanisms to quantify the appearance of key words configured by users of the service. Another possible approach is to use commercial advanced text-mining, which offer very advanced text processing techniques that can identify statistical parameters and perform linguistic sentence grouping. Such tools have powerful mechanisms to quantify and extract statistics about impacts (mentions of the terms of interest) and to draw up metrics such as the return on investment in promotion. They can also extract information on the polarity of opinions (sentiment analysis) over time, thus enabling visualization of trends, especially in concepts such as brands.

There are, however, limitations to the commercial solutions available today because, for example, these tools does not take into account the context or the semantic relations between concepts in the agrifood domain in general, nor possible customization in, for example, sauces, industrial baked products or snacks. This is key for correct interpretation of the information captured and expressed freely in social media, blogs, publications, etc. because of the semantic richness with which opinions are expressed about foods, food culture (hedonism, sensory appreciation, etc.), and the impact on people and on their health.

Moreover, most solutions are mainly oriented toward activities related to marketing and product positioning rather than to the generation of an overview of the status of opinion, threats, and opportunities for innovation in a sector like food. Also desirable for the food sector would be qualified associations relating to consumers' assessments of a product based on its ingredients and other food concepts. Such aspects are important, for example, for anticipating reputational crisis (as with palm oil in processed products) or for reacting in time to a change in formulation without waiting for demands from retail or from consumers themselves, or just for detecting potential threats for a specific product or product category imposed by a group of social media influencers.

Although great progress has been made in the development of deep learning technologies applied to the processing of texts in natural language, there are not yet any specialized commercial solutions for detection like those described above, at least nothing specific for the agrifood sector.

5 Description of Current Solutions Related to Small/Big Data and Machine Learning

Having introduced the current situation of commercial technological solutions for managing food quality, microbiological control, and product innovation by active listening in digital media, the following section describes the impact that AI can have on each of these key processes in the agrifood industry. We also describe some real applications on which the authors have been working in recent years.

5.1 Application of AI in Production Quality Control

As already stated, quality control in food production aims to achieve homogeneity, optimization, and efficiency and to reduce complaints and waste in the industrial stage. Given the general complexity of production processes, in which there are great interactions between different processes, modeling them all using mechanistic methodologies based on equations or what are often differential equation systems is very risky because of the accumulated simplification in the models and because such methods do not take into account the interactions among the processes themselves and their effects on the product.

Black-box models (MIT Technology Review, 2020), also known in the industry as Response Surface Modelling (Myers, 2016), collect data on the production environment that are sufficiently variable and can relate decision variables, that is, those that can be controlled by operators or production managers, with the variables that characterize the finished product. Such models can be used, for example, for prediction (or "prognosis") of product quality on completion in a specific production configuration. The terms "black box" or "response surface" refer to the intuition that the data processing techniques will generate a type of mathematical model that can model the reality that is described by the data but that cannot be accessed or understood by the experts. Supervised machine learning and deep learning, as a customization of the former, are paradigmatic examples of black box models. Their main advantage is that they can model beyond individual processes and deal with very complex problems such as a dynamic production environment. In industrial prognosis, for example, they can predict the quality of a given product. Machine learning techniques such as convolutional neural networks (CNN) (Yan et al., 2019) (widely used in other fields such as image processing or natural language processing) or recurrent neural networks (RNN) (Xia, 2020) can also be used in predictive equipment maintenance.

For global simulation of a line, there is a wide range of techniques that have been tested to different extents in controlled industrial environments but there is not yet a clear consensus on what functions best in different production contexts. Moreover, there are new families of machine learning techniques that have been widely used in automatic learning in images and in natural language, especially in the field of deep learning, such as convolutional neural networks, the introduction of Transformers (Perez et al. 2019) as layers of a deep neural network, or neural network techniques with LSTM (Long Short Term Memory). The first two of these might be very promising for managing sequential information if transferred to other fields, but this aspect has not yet been sufficiently explored in the bibliography consulted by the authors regarding the production environment, and even less so in food production.

5.1.1 Case Study of AI Applied to Food Quality Control

Description of the problem: In a hamburger bun production environment, the main consideration for quality is the evenness of the surface of each unit regarding color continuity and the actual color when cooked. The main problem is that, sometimes and in a way that cannot be controlled by the operators, some batches come out of the oven with a darker color, even though there have been no significant changes in the process variables.

Solution proposed by AINIA (see Fig. 1): Production data were collected over 1 month of production, taking into account variables such as oven temperature, time in the oven, prior fermentation time, and humidity and temperature during baking together with other data coming from different information systems. Taking these data and the quality variable, that is, the surface color, we implemented one machine learning model using neural networks and another using the XGBoost random forest technique.

Results: After various iterations to refine the hyperparameters of these two techniques, we obtained success rates with the neural network model of about 65%, and the random forest model was able to identify a decision tree but none of the variables

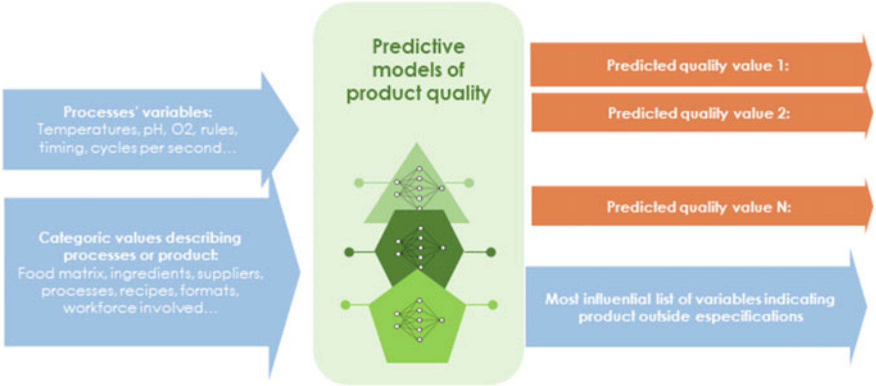

Fig. 1 Schema of the AI solution for predictive models of food product quality

stood out especially. That is, it was not possible to explain the baking phenomenon using the current variables. After conversations with the line operators, we identified the intuition that the oven gas burners might be related to the degree to which the buns were baked. We captured signals on the degree of opening of the 4 burners and on about 300,000 product samples (pans of buns), then again generated and re-trained using the two techniques: neural networks and decision trees. In the first case, we were able to raise the success rate of the prediction of baking to 80%; in the case of the decision tree, we found that the degree of openness of 2 of the burners determined the optimal conditions for baking. After this experiment, the procedure for opening the burners was changed by the company, making it gradual to minimize this effect. This reduced the number of rejected, overcooked buns by almost half.

5.2 Application of AI to the Management of Food Safety Risk

As stated above, industrial food safety risk control is a complex process because many parameters are involved: hygiene protocols, hygiene design of equipment, cleaning protocols for workers and the environment, presence of microorganisms in the environment, temperature and humidity conditions in the plant, origin of raw materials, specific processes to eliminate microorganisms to varying extents, packaging processes, and other variables in the product such as water activity, which may be very relevant for determining risk. Controlling food safety risk in a very dynamic and uncertain environment is very different from the traditional use of predictive microbiology on which current models have been developed, in controlled laboratory conditions. Intuition led us to believe that black box models would be able to integrate all this complexity, which in most cases cannot be linearized. This was a potential technical option although it would probably require a large amount of data samples, depending on the type of microorganisms whose presence is to be modeled.

For black box models, that is, those based on machine learning, several references were found but none for the production environment. They were more an extension of the controlled laboratory conditions of previous models: for example, we found references to prediction of *Listeria monocytogenes* (Gosukonda et al., 2015; Oladunjoye et al., 2017), a pathogen of interest for the industry, with general modeling using neural networks in controlled production conditions (Fernández-Navarro et al., 2010), and risk prediction with machine learning associated with HACCP data in a meat firm (Kaiyi et al., 2007).

Machine learning has also been used in the context of food safety, not to identify production risks but to detect the existence of microorganisms or of chemical spoilage in the actual product. Other applications of machine learning come from the field of natural language processing and aim to identify public health events from text analysis (Geng et al., 2017, 2019) in digital media of different types.

A field on which AINIA is working is the exploration of current deep learning techniques with the aim of building predictive models that can represent with sufficient expression the phenomena that arise throughout production and shelf-life, and their effect on the presence/growth of microorganisms. Among the techniques analyzed and tested, there are some that worked well in contexts such as natural language processing, in which a time component was introduced in the information coming from the samples:

- Long Short Term Memory neural networks (LSTM (Hochreiter & Schmidhuber, 1997)) are a sort of Recurrent Neural Network (RNN (Mikolov et al., 2010)). They are characterized by the fact that it is possible to do feedback among their perceptrons, generating a certain memory in the network itself. They are thus ideal for processing and predicting time series, which are some of the elements that arise in data collection in a production environment. LSTM are being used successfully to predict product demand (Abbasimehr et al., 2020) and prices, but no bibliographical references have been found applied to the prediction of microbiological risk in a production plant environment.
- Back Propagation Neural Networks (BPNN). One study has been found in the bibliography (Deng et al., 2019) using these to predict the presence of coliform bacteria in food, in the framework of a multidimensional problem and with categoric (non-numerical) information such as the representation/presence of certain ingredients and variables such as pH and temperature.
- Convolutional Neural Networks (CNN). In recent years, these have been used in the field of deep learning in image recognition, because they can break down the detection problem into specialized layers that decide about specific characteristics (e.g. contours, fillings, blurring, etc.). In the area of food, they have been used, for example, to classify fruit (Pan et al., 2017) or to identify food safety problems (Jiang et al., 2019).

The above techniques are the most promising in the state of the art of deep learning and, for the current prediction problem; research is focusing on identifying which of them can achieve the best results. These may differ from one firm to another. Although traditional machine learning techniques are not being set aside such as the initial working approach, nor others that might look promising throughout the life of the research project, the results of such techniques (e.g. assessment using ROC curves) will be tested and compared, iterating tests with the processed data and hyperparameters until optimal predictive capability is achieved.

When supervised machine learning or deep learning techniques are used, the development of models is associated with a set of data obtained under certain conditions using a set of techniques and their associated hyperparameters. This means that subsequent use of the model with, for example, predictive purposes, must be done on a system that generates data under the same conditions as those under which the original data were generated. For production, this means that, if we capture information on a specific production line with its unique characteristics, the model will not function if tested on another line, which amounts to a wasted investment on generating the samples in terms of both time and cost. This, precisely, is the context in which Transfer Learning (Pan & Yang, 2010) becomes necessary. The aim is to have a trained network with a prior data set, which can be re-trained with specific data sets. One of the main advantages is that, if we start out with a model trained in the same area, the number of samples to be included in the new 'transferred' model will be smaller than if we were to develop the model from scratch. Classic examples of this type of technique are Word2vec (Tensorflow, 2022) in the field of natural language processing or VGG-19 (Kaggle, 2017) in image processing.

Another type of technique that is potentially effective is Reinforcement Learning (Nguyen et al., 2020) Here the aim is to make an agent learn from actions performed and feedback provided to it on whether the action was correct or not (Sutton & Barto, 2018). Such techniques are being used for learning in gaming. The intuition is that a production environment can be governed like a game, that is, decisions can be taken on consignments, reference units, alarms, process times, etc., and the effect is the potential appearance of microbiological risk in the finished product or during its shelf-life. Some of the algorithms associated with such techniques are Q-learning (Melo 2001) and SARSA (Dilipkumar, 2020) (State-Action-Reward-State-Action). Reinforcement learning techniques can also be used, for example, in problems where there is not a large number of samples, and if the aim is to reinforce or penalize some samples but not others.

5.2.1 Case Study of AI Applied to the Management of Microbiological Risks

Description of the problem: On a production line for Group 4 vegetables (lettuce, cabbage and other cut and prepared salad vegetables), there may be episodes when *listeria monocytogenes* could be present. Current HACCP methods cannot identify the main cause of this presence in the production process. Since the product is fresh, sterilization processes (such as heat treatment) are not possible because they would impair the product. The aim is to identify the current risk (high, medium, or low) that the product might contain the microorganism in the current conditions on the line.

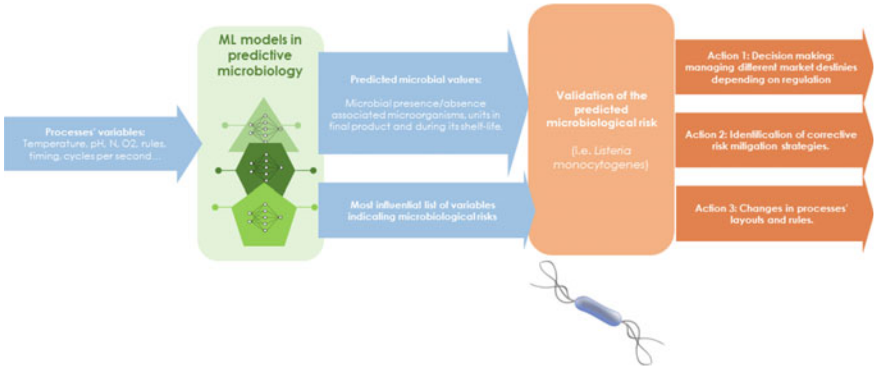

Fig. 2 Schema of ML models in predictive microbiology

Solution proposed by AINIA (see Fig. 2): The proposal was to capture process data linked to the presence of the microorganism and environmental data that might contribute to it: ambient temperature, temperature and pH of washing water, drying process control, percentages of gases during controlled-atmosphere packaging, original supplier of the raw material, and types of raw material. For example, we had the intuition that certain vegetables 'hide' listeria better than others did and, of course, the presence/absence of the target microorganism captured using laboratory techniques, or of other harmless microorganisms that behave in a similar way. There are two main complications. First, there is little capability for generating a large number of samples because the process to find the presence/absence of the microorganism in some cases may require hours or days and also it has a high cost (5–20€ per analysis) compared with acquiring data from a sensor (practically 0€). Second, there is high dimensionality because of the number of factors that may affect the presence of the microorganism. Moreover, the combination of these two drawbacks amounts to a statistical challenge when managing the samples to which the microbiological risk predictive model is to be applied. Therefore, we identified techniques that could function with a small number of samples and are studying the capacity for generating samples of a synthetic nature, in line with historical knowledge on the line and previous records. We are also analyzing techniques to reduce dimensionality in non-linear problems in order to reduce the number of variables to be taken into account in the model. We are beginning with classic neural networks and plan to migrate to Back Propagation solutions which, according to the bibliography, have worked well, and we shall test new configurations using Reinforcement Learning techniques to support the lack of samples.

Results: At the time of writing, we do not yet have conclusive results allowing us to choose one technique rather than another.

5.3 Application of AI to the Extraction of Knowledge from Texts Referring to the Market and the Sector

In this third area of application of AI techniques in the food sector, we face a problem that falls outside production but is very relevant for food firms because it directly affects the detection of opportunities for innovation or of food safety risks based on monitoring the environment, in this case, the digital media environment.

The general goal is to extract knowledge published in digital media such as social media, professional publications, and generalist media that more or less specialize in the food sector. From the technological point of view, the goal is to classify and quantify texts and publications in certain categories that can add knowledge to certain incipient signs identified by an expert.

For this type of problem, any references on technical advances come from research. The sources on which these techniques are used in the sector are of various types: social media (Twitter), publications in specialized journals, blogs, publications by leading public agencies, etc. In all of them, natural language processing techniques are used. Since the objective is to establish deep learning models allowing for the classification and processing of captured texts, the first step is always correct preparation of the texts using techniques such as stemming (taking the semantic root of the words) and tokenization (dividing long texts into smaller units for processing). To create the models, word embedding techniques are used to allow terms and concepts to be represented as multi-dimensional vectors so that they can be properly processed by deep learning.

Some initiatives such as Injadat (2016) and Lee (2018) have identified working formulae for the classification of texts and publications, and neural network techniques (the basis of deep learning) and vector support machines have been identified as the most promising for texts coming from social media. Another interesting discipline for solving this type of problem is "opinion mining" (Pournarakis et al., 2017), that is, techniques to extract opinions from texts published by users and to associate them with the concepts that appear in such texts.

Another approach in the field of social media mining is to try to identify crises and threats from rumors. An initiative by Chen (2018) tries to identify rumors in social media not from a classification system approach but as an anomaly detection problem, by searching for changes in the pattern of communication of individual users.

Today the most usual solutions for this type of problem are grouped in 'ensembles', which combine various techniques, observing the results and providing a final solution for each problem. The most promising solutions that have obtained the best results in leading competitions in machine learning (https://www.kaggle.com/) combine various ensembles to achieve high-precision classification.

In the area of food, organizations such as the European Food Safety Agency (EFSA) and TNO have attempted to identify risks emerging in food from proof of concept using semantic technologies to identify relations between the appearance of key words in the abstracts of scientific articles and an ontology of food safety risks.

Today, two families of machine learning models are appearing for possible application to natural language problems, adopting a new approach and searching for the limits of modeling using revolutionary neural network techniques. One type of algorithm is Bidirectional Encoder Representations from Transformers (BERT, 2019), proposed by Google. This natural language model is a pre-trained model with a large amount of texts in English. It is unique in that it is based on unsupervised training with a Wikipedia text and 800 million words from a book base. It differs from traditional methods in which models such as Word2vec can generate a vector representation for each of the words it trains without taking into account the context (previous or subsequent words or sense of the text). For example, in English the word "right" would have the same representation in the sentence "*I'm sure I'm right*" as in "*Take a right turn.*" The main novelty is that BERT can represent the word "right" in its different senses because it creates the bidirectional concept, that is, the representation of the word takes into account the previous and subsequent words in the text, and this can be implemented by deep, bidirectional neural networks. The main advantage is that, based on this language training and with few samples, it can be adapted to a specific domain that we are interested in, such as discovering knowledge in the agrifood sector. The second main reference in this type of algorithm, which is also used in other contexts such as image recognition, is GPT, currently active in its versions GPT-2 and GPT-3. It is promoted by OpenAI (2019) whose principles take their inspiration from BERT, but it stands out for its capacity to predict the next word in a sentence or to complete words lost in a text, whatever the domain. The OpenAI team has released versions of this model but they are limited and go together with an open access article that describes the AI methodologies, mainly Transformers technology, which can establish relations between words following a given time line and an order when representing them.

5.3.1 Case Study of AI Applied to Supporting the Discovery of Emerging Risks in Food

Description of the problem: Specialists in the field of emerging risk detection in the food industry perform periodic reviews of hundreds of documents published in different sources to identify signs that might support an emerging risk hypothesis that they have identified a priori. This process sometimes leads the experts to analyze documents whose title seems to associate them with a specific risk but which turn out to be unrelated to that risk or any other, so reading them has been a waste of time. Therefore, to have a system that classifies incoming texts a priori into pre-set categories would save a lot of time and effort. Emerging risks are usually associated with regulatory trends on ingredients or products used by the industry, but may also be associated with risks that a product might be rejected in a market in relation to a reputational crisis of an ingredient or a product category, or even a negative association of a commercial brand in publications in social media.

Solution proposed by AINIA (see Fig. 3): Development of a computational model for text classification based on machine learning and on the Word Embeddings

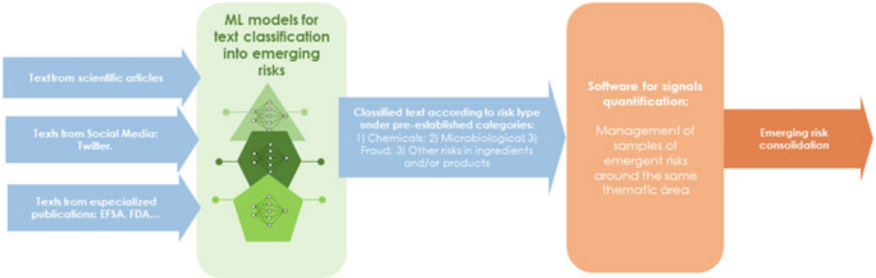

Fig. 3 Schema of ML models for text classification relating to emerging risks

methodology combined with neural networks. For this purpose, we trained more than 10,000 texts from about 500 different sources of articles and tagged them in four different categories of food risk (chemical, microbiological, fraud, ingredients, or products) plus one more for rejections, that is, to indicate that the text does not refer to a risk.

Results: The classifier achieved almost 95% precision in text classification. This reduced by half the time the experts devoted to identifying risks, minimizing the time to read articles not associated with a food risk. There is still room for improvement by increasing the number of samples in the model and adopting a system that will allow for periodic, semi-automatic updating. This aspect is to be covered in subsequent stages of the initiative.

6 Summary of the Main Advantages of the New Solutions, Benefits Obtained and Expected Future Benefits

6.1 Main Advantages

The areas of interest analyzed above focus on key activities in the food industry such as quality control in the production plant, food safety, promotion of product innovation, and analysis of threats for products. In all of them we have identified potential impacts and advantages for the sector, which can be summarized as follows:

- Improved perception of quality by consumers and customers of food firms: Adopting AI to establish links between production conditions and a product's target variables is key for standardizing optimal production conditions and promoting quality while adjusting aspects such as cost.
- Standardization of production conditions: AI can help detect the most favorable conditions so that they can be maintained or the least favorable so that they can be avoided.

- Waste reduction: AI can monitor production to minimize product rejection and to improve sustainability by saving the energy used on products that would not reach the market.
- Fewer quality complaints: When products are standard and within specifications, there are fewer quality complaints from customers and consumers. This avoids the cost of product withdrawals and a negative impact on the brand image.
- Fewer product safety crises: By monitoring the risk of microorganisms appearing that might impair quality or safety in both perishable and non-perishable food products in real time, AI allows for progress away from a reactive microbiological monitoring model following certain HACCP parameters to a model based on quantification, monitoring and management of risk.
- Improved decisions on product destination. AI can help in decisions about the destination of products that involve a potential risk. For example, risk can be classified as low, medium, or high, so products with an acceptable level of risk can be sent to markets where it would be legally permissible.
- Risk mitigation. AI techniques can identify the main causes behind a quality or food safety problem in a product or during its shelf-life. This allows for policies to be adopted that will mitigate the most relevant of these.
- Identification of innovation opportunities in line with market demands and with trends in the sector. AI can help filter, process, classify, and quantify information found in texts published in digital media. It can help identify product launches by other firms in similar product categories and can identify the degree of innovation of competitors and of the market in which a firm operates, in addition to many other analyses that can promote a firm's innovation strategy.
- Identification of threats to a firm's products that might have an impact on its strategic plans for innovation and product development. In opposition to the previous point, AI can identify the paths that a firm should not follow in its market strategy: avoiding unacceptable complaints from consumers or the market, avoiding specific ingredients or suppliers with a questionable reputation, and avoiding the effect of regulatory changes on products in the short and medium term, among many other aspects of risk monitoring.

In addition, there are other areas of the agrifood sector in which the application of AI might be of interest:

- Simulation of bioprocesses: These are techniques used to model advanced biological processes at human level (e.g. digestion models) and microbiological level (e.g. microbial fermentation processes as in wine and beer) or to model processes to create by-products such as biogas or proteins.
- Agronomic models for crop growth and production: Data-based machine learning models can be used to predict the volume of an agricultural product that a specific plot or farm can generate in the short, medium, or long term.
- Simulation of product demand: Algorithmic techniques are being devised that stress historic time series in order to predict the future behavior of a signal based on models that take into account this time component. For example, after eliminating

the effect of exceptional situations or anomalies, historic data on sales can be used to predict future demand for a product category.

7 Conclusions

In the application of AI to the food sector, the most important trends that will determine specific areas of research will focus on certain technical and technological challenges inherent in the nature of the problem, the context of use, the type of data and the capacity of producer firms to correctly sample data by following procedures and storing them in a structured fashion. The challenges identified for progress in the application of such technology to the industry are the following.

Complexity for aligning data samples: Firstly, in order to draw up a predictive model using deep learning techniques, it is essential to digitally characterize a product sample that has been through a set of production processes so that microbiological analysis can be performed or quality parameters monitored at different points in the production process and/or during the product's shelf-life. Total digital tracing of all the relevant parameters depends to a large degree on the preparation of the firm's information systems, and on the construction of software components that can align the data and link them for subsequent use. A lack of data or a rejected data sample may invalidate the data for a model. Also, this amounts to a major organizational and technological challenge for firms, especially for small or medium firms which are the majority in this sector. It is essential to work with production and quality experts to establish the logic for allocating certain process data to a specific sample.

Secondly, when modeling, the time component of, for example, a baking or curing process may affect not only the conditions of the current product but also which products were produced before or how long the process has been under way. The success of this phase of data sample alignment determines the success of the predictive model and requires effort and decision-making and, in some cases, will be based on trial and error. Aligning samples by process, product quality, or food safety variables may become a useful technological starting point for many other applications related to product improvement or other microbiological or quality risks for firms and may amount to a differentiating element and progress toward advanced use of the digitalized data.

Limited references on deep learning in dynamic industrial contexts. Many references to deep learning techniques are available in the research community but very few can be found in dynamic industrial contexts and practically none in the field of food safety. It is therefore a challenge to consolidate certain cutting-edge techniques that might be appropriate for solving common problems and achieve acceptable levels of success in prediction (prognosis) and in simulation of production processes. There is not yet a consensus in this regard among the research community either for industrial sectors in general or for the food sector in particular. This means that the adoption of AI in industry is still under-developed in comparison with other methods such as image processing or natural language.

Money and time constraints for collecting and processing good-quality microbiological samples. Microbiological information and much objective data on quality parameters come from laboratory analysis so require sample processing, reagents, and time to analyze each microorganism or quality parameter. While obtaining process data is relatively cheap because of the use of sensors and actuators on production lines, it is not so easy or so cheap to automatically obtain information on quality variables. This drawback is inherent in the development of specific models and has to be resolved using strategies based on generalist models and on specialization using small data samples in a specific product category.

"Imbalanced classes" (Krawczyk, 2016): In a food production environment, most of the products are usually sold with good microbiological and product quality within the specifications. Obviously, products with microbiological spoilage or with impaired quality may appear occasionally, but this is rare. In the case of pathogens, this scenario is especially acute because production processes are designed to minimize them, although such elimination might be less effective in fresh products. Therefore, if we set up a data sample collection process in a production environment, most of the samples captured will meet specifications so will be of little interest for helping to solve problems. Also, there will be few samples and the data will not be very representative of problems that might arise on the line. This problem is known as "imbalanced classes" and there are techniques that can correct it under certain conditions. However, more work is needed on them as this is a real problem that will become more important in the future.

Multivariance with large numbers of variables. The many variables considered may include categorical, non-numerical variables such as ingredients, suppliers and other types of product information that may have an influence on the shelf-life of products. When developing predictive models, there should be a balance between the number of variables that describe the data in a sample, and the number of samples available for modeling. Predictive models will be simpler and more likely to show good predictive behavior if they include a small number of variables that are very significant in the process. In order to achieve success in this context, multidisciplinary teams are needed to identify the variables and parameters that are really causing the phenomenon to be modeled, avoiding signals that might interfere with the technological capability of the models for describing the reality.

Explainability of predictive models: It is currently being found in the AI scientific community that techniques such as neural, or black box, techniques do not afford good explainability of predictive results nor of what happens internally in the decision-making processes of the neural network. That is, if decisions are taken based on AI algorithms, it is not fully understood exactly why certain results are reached. This is what is known as Explainable Artificial Intelligence (XAI) (Arrieta et al., 2020). It is very important to work on the explainability of models in order to help resolve the problem of mitigating microbiological risk in order to learn more about the most effective opportunities for risk mitigation. It is also important from an ethical point of view because there is debate on whether what algorithms can process and present can be believed because, if there is any bias in the data, any predictive algorithm will include the same bias. Such a bias would exist, for example, if, when analyzing social media, we only take into account opinions on certain brands and products that are not available to all, omitting a certain group. This would result in an erroneous strategy if, for example, that group is the usual customer base for the product being studied. Work is also being done on grey box models which reinforce black box knowledge with data based on real expert knowledge. This results in a more powerful working base, overcoming to some extent any polarity introduced by certain data groups.

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