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COMPREHENSIVE REVIEWS IN FOOD SCIENCE AND FOOD SAFETY

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Application of machine learning to the monitoring and prediction of food safety: A review

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Abstract

Machine learning (ML) has proven to be a useful technology for data analysis and modeling in a wide variety of domains, including food science and engineering. The use of ML models for the monitoring and prediction of food safety is growing in recent years. Currently, several studies have reviewed ML applications on foodborne disease and deep learning applications on food. This article presents a literature review on ML applications for monitoring and predicting food safety. The paper summarizes and categorizes ML applications in this domain, categorizes and discusses data types used for ML modeling, and provides suggestions for data sources and input variables for future ML applications. The review is based on three scientific literature databases: Scopus, CAB Abstracts, and IEEE. It includes studies that were published in English in the period from January 1, 2011 to April 1, 2021. Results show that most studies applied Bayesian networks, Neural networks, or Support vector machines. Of the various ML models reviewed, all relevant studies showed high prediction accuracy by the validation process. Based on the ML applications, this article identifies several avenues for future studies applying ML models for the monitoring and prediction of food safety, in addition to providing suggestions for data sources and input variables.

KEYWORDS

Bayesian network, chemical, contaminant, hazards, model, pathogen

1 | INTRODUCTION

Along the food supply chain, food products may become contaminated with various types of safety hazards, including biological hazards (e.g., bacteria, viruses, and parasites), chemical hazards (e.g., heavy metals, pesticides, and mycotoxins), or physical hazards (e.g., metal fragments and pieces of glass) (van der Fels-Klerx et al., 2015). The presence of these hazards can affect the safety of food or feed products, with potentially detrimental effects on human and animal health (ISO, 2016). Monitoring potential food safety hazards along the entire food supply chain is important in order to guarantee the correct functioning of food safety management systems (ISO, 2013) and thus the safety of food and feed (Focker et al., 2018; van Asselt et al., 2018). In this context, food safety monitoring is defined as the mechanism of conducting regular inspections for the presence of food safety hazards in order to verify that procedures are being executed correctly and that food safety regulations are being followed properly. A monitoring plan that describes what will be monitored (including which food products and which food safety hazards) and how this will be done (including how many samples will be collected and how they will be prepared and analyzed) is essential to the implementation of food safety monitoring. Food safety prediction here is defined as a model-based process that seeks to predict future food safety events or outcomes by analyzing patterns from historical food safety and other related data. The process of setting up food safety monitoring plans, and particularly the parts relating to identifying the products and hazards that should be assessed, could benefit from early warning and predictive modeling approaches (Geng et al., 2017; Liu et al., 2010). Such approaches can make use of historically collected monitoring data, as well as previous experiences and other available information, and use these to provide an assessment on the food safety hazards and/or products that should be prioritized for monitoring, as well as on when and where monitoring should be performed along the food supply chain. Combining various types of information and using these in prediction approaches could improve the quality and cost-effectiveness of monitoring and the reliability of prediction of food safety hazards. The White Paper on Food Safety published by the European Commission (2000a) states that the integration of data sources on food safety and the analysis of such data are the two guiding principles for comprehensive and effective food safety monitoring.

Machine learning (ML) is a relatively new method that has been proven to be capable of combining various types of data, including structured data and unstructured data[1] (Géron, 2019), in this case relating to the presence of food safety hazards to make predictions about food safety. With ML, computers are programmed to "learn" from input data available to them. Learning is the process (based on a learning algorithm) of converting the input of experience (e.g., historical data) into the output of expertise (e.g., classification and prediction) (Alpaydin, 2010; Murphy, 2012; Shalev-Shwartz & Ben-David, 2014). ML models for purposes of monitoring and predicting food safety have been used in several studies (Bouzembrak et al., 2018; Geng et al., 2017; Liu et al., 2018), demonstrating ML modeling is a promising tool for addressing the task of food safety monitoring and prediction.

Although the use of ML models can assist the tasks of monitoring and predicting food safety, they are not widely applied within this context. Important reasons include (1) the very recent and rapid development of ML methods; (2) the dispersion of data relating to food safety across the domains of food, health, and agriculture, as well as other domains that are less directly related to food safety, which complicates the selection of data sources (Marvin, Bouzembrak, Janssen et al., 2017); (3) the difficulty of determining which variables can be linked together for ML modeling in order to achieve satisfactory results; and (4) food safety records are still not digitized in many cases making it difficult to use such records for ML. Several reviews are available on ML applications to food safety. A recent overview presents emerging ML applications in food safety mainly focusing on foodborne[2] pathogens and foodborne disease (Deng et al., 2021). Other reviews present deep learning applications in food (Zhou et al., 2019), ML techniques using text mining for food science and nutrition (Tao et al., 2020), and ML applications on tracing the source of foodborne disease (Wheeler, 2019). Finally, one review focuses on data derived from nondestructive[3] food analytical techniques (Ropodi et al., 2016). However, an overview of ML applications in monitoring and prediction of food safety is not yet available.

To facilitate the application of ML within the context of food safety monitoring and prediction, and to provide insight for future studies, this article presents a literature review aimed to retrieve relevant ML applications to food safety, to categorize and summarize ML applications in this domain, to categorize and discuss data types used for ML modeling, and to provide suggestions for data sources and input variables for ML modeling. This review provides a starting point for future studies that wish to apply ML to food safety monitoring and prediction.

2 | MATERIALS AND METHODS

2.1 | Literature search

The literature search focused on studies applying ML models within the context of food safety monitoring and prediction. A systematic literature review was performed according to the guidance of systematic reviews developed by the European Food Safety Authority (2010). The review focused on peer-reviewed publications published in English in the period from January 1, 2011 to April 1, 2021. Three different electronic databases were used to collect the relevant publications from the scientific literature: Scopus, CAB Abstracts, and IEEE. These databases were selected to provide a sufficiently large initial sample of relevant articles. The type of publication was restricted to

[1] The definitions of structured data, unstructured data, and ML algorithms are explained in Section 3.

[2] Foodborne: caused by contaminants, such as toxic substances or pathogenic microorganisms, in food.

[3] Nondestructive: technique that does not involve the removal of a sample.

published peer-reviewed primary research articles from journals with an ISI impact factor. The database search was performed in April 2021. Search strings and selection criteria were predefined and adjusted during the search, when necessary.

2.1.1 | Search criteria and search strings

The search focused on studies on ML model applications in food safety monitoring and food safety prediction. A combination of search terms was applied to the title, keywords, and abstract of the publications. The search strings include subclasses for the various types of ML models: "machine learning" or "artificial intelligence" or "deep learning" or "supervised learning" or "decision tree" or "random forest" or "naive bayes" or "bayesian network" or "bayesian belief network" or "support vector machine" or "ensemble method" or "ensemble learning" or "boosting" or "gradient boost" or "bagging" or "k-nearest neighbor" or "neural network" or "unsupervised learning" or "principal component analysis" or "k-means" or "association rule" or "clustering method" or "association rule learning" or "semi-supervised learning" or "reinforcement learning" or "q-learning" or "temporal difference" (Ru et al., 2017). The general term "food safety" was included in the search strings, even though the focus of the study was monitoring and predicting food safety hazards/risks. This was due to the difficulty of clearly defining the search strings relating to these specific aspects of food safety while not excluding too many relevant articles. The use of more general terms yielded a larger set of references, which were then screened for relevance to the topic of the study in the next step.

2.1.2 | Search process

The selected relevant references were collected and stored in an Endnote file, which was used as a working database for storing the initially retrieved set of references and for sorting the included and excluded references based on the application of the aforementioned selection criteria. References retrieved from the various databases were combined and subsequently screened in the following steps: (a) duplicate references were removed; (b) both relevant references and "possibly relevant" references were selected—and nonrelevant references excluded—based on reading the title, keywords, and abstract, using the selection criteria mentioned above; (c) the groups of relevant references and "possibly relevant" references were then further evaluated by reading the full texts, and those that met the selection criteria were retained. Following the suggestion of reviewers, several valuable articles suggested, not containing the abovementioned search strings but relevant to our topic, were added. All studies meeting the selection criteria were retained and used in the present review.

2.2 | Classification of the relevant publications

The studies included in the final selection were classified into categories according to their field of application, type of data used, and type of ML model used.

3 | RESULTS AND DISCUSSION

3.1 | Literature search

The literature review process yielded a total of 1162 initial references, including 804 from Scopus, 299 from CAB Abstracts, and 59 from IEEE. From the initial set of references, 125 duplicate references (due to the use of three databases) were eliminated. Evaluation of the remaining 1037 references yielded 210 (possibly) relevant references (including relevant and possibly relevant articles). After reading the full text (or parts thereof) of these 210 articles, 114 references were selected as relevant and were used in the further analysis of this study.

3.2 | Overview of studies

An overview of the selected publications (numbers per year and per food safety hazard type) is presented in Figure 1. As can be seen from this figure, most articles have been published in the period 2017–2021 (until April 1, 2021), showing that the use of ML models for the monitoring and prediction of food safety has been growing rapidly in recent years. With regard to the type of food safety hazard studied, 36 of the included studies focus on biological hazards, 22 studies on chemical hazards, two studies on physical hazards, 16 studies on food fraud, and 38 studies on general or other aspects of food safety hazards.

Figure 2 shows the classification structure of the relevant articles, with selected publications classified into four categories of application: 60 articles focused on prediction and monitoring of one or some specific food safety hazards, 38 articles focused on prediction and monitoring of food safety hazards and events in general, 16 articles focused on food fraud, and 10 articles focused on traceability of food safety hazard in general. Data types used were classified into two groups: 48 articles focused on structured data, and 66 articles focused on unstructured data. ML algorithms mostly used for analyzing structured data

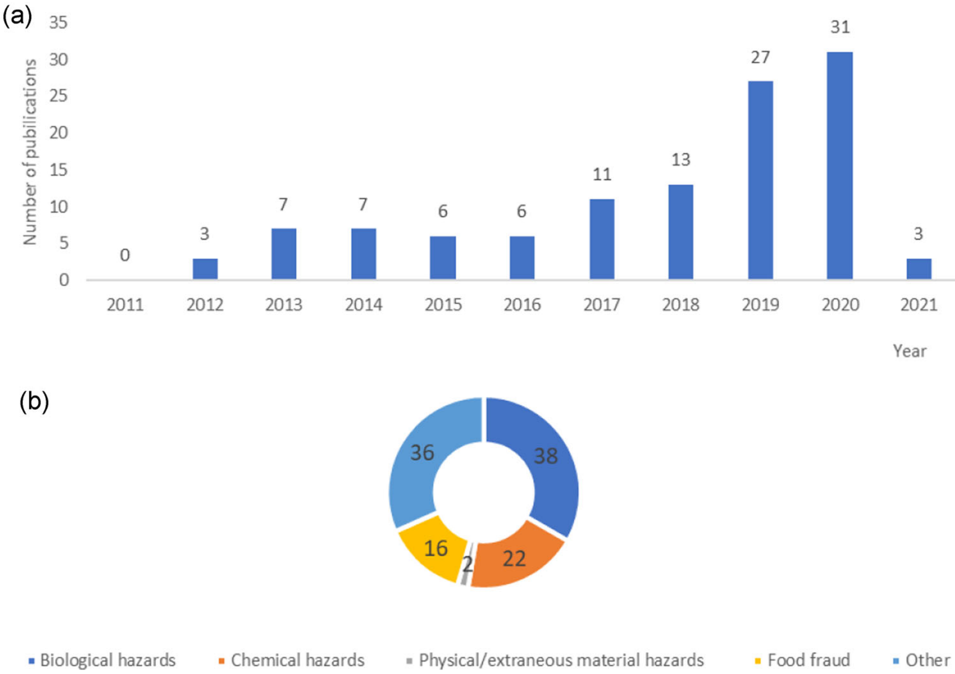

FIGURE 1 (a) Number of selected publications per year. (b) Number of selected publications per hazard category

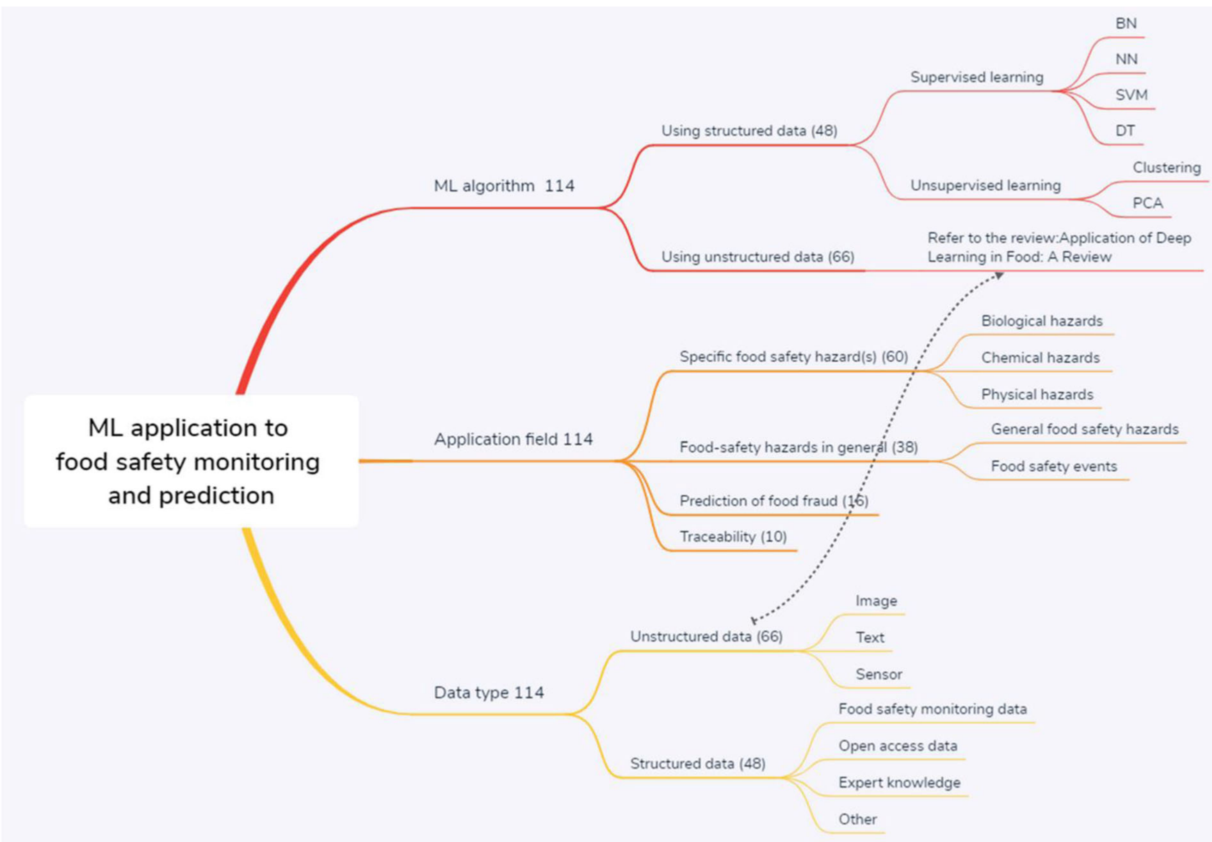

FIGURE 2 Classification structure of the relevant literature

were Bayesian network (BN), Neural network (NN), Support vector machine (SVM), and Decision tree (DT). ML algorithms mainly used for analyzing unstructured data included various types of NN. In Sections 3.3–3.5, results of the evaluation and classification of the articles according to ML model type (Section 3.3), food safety application field (Section 3.4), and type of data (Section 3.5) are reported and discussed, along with examples for each classification category and the main practical significance of the studies.

3.3 | Introduction of ML algorithms

3.3.1 | ML algorithms using unstructured data

The most frequently used ML algorithms to analyze unstructured data include various types of NN. For example, convolutional neural network (CNN) is used to analyze image data and recurrent neural network (RNN) is used to analyze text data. The ML algorithms used to analyze unstructured data related to food safety have recently been reviewed by Zhou et al. (2019). The reader is referred to this review for detailed information.

3.3.2 | ML algorithms using structured data

Of the ML models covered in our literature search, the relevant studies mostly apply four different basic ML models being BN, NN, SVM, and DT, as well as various combinations of these basic ML models (e.g., PCA combine with NN), ensemble model (e.g., random forest [RF]), or various derived model types (e.g., extreme learning machine [ELM]). This section provides a brief introduction to each of the four basic ML methods used in the selected publications. Examples from the publications retrieved are presented to provide an overview of the validation accuracy of the ML model.

Bayesian network

A BN model (including the Bayes classifier) (Bouzembrak & Marvin, 2016; Bouzembrak & Marvin, 2019; Bouzembrak et al., 2018; Liu et al., 2018; Marvin, Bouzembrak, Hendriksen, et al., 2017; Marvin et al., 2016; Sun et al., 2013) is a graphic model containing nodes (with corresponding probability distributions) representing variables and directed arcs connecting the variables (with conditional distributions) (Nielsen & Jensen, 2009). A conditional distribution is assigned between each node category and its parent nodes. The probability distribution of each node can be obtained from expert opinion, statistical models, empirical data, simulations, reports, or articles (Buriticá & Tesfamariam, 2015). A BN is able to describe the interactions between variables, in addition to quantifying and characterizing complex outcomes (Nielsen & Jensen, 2009). It is a supervised model for both regression and classification problems, and it is easy to understand and capable of dealing with incomplete datasets. The structure of a BN model can be built according to expert opinion, and it can be supplemented with variables incorporating managerial decisions (Bouzembrak et al., 2018; Liu et al., 2018; Uusitalo, 2007). Liu et al. (2018) apply a BN model to predict the level of the mycotoxin deoxynivalenol (DON) in wheat in the Netherlands using an incomplete input dataset. The results indicate an accuracy level of 86% for the BN model. In an exploration of a BN modeling approach, Marvin et al. (2016) apply expert knowledge to predict the occurrence of food fraud incidents. The level of model prediction accuracy was 91.5%. Results demonstrate how expert knowledge and quantitative historical data can be combined within a model to help risk managers to identify the factors that influence food fraud and to improve understanding concerning interrelationships between these factors. Bouzembrak et al. (2018) develop a BN model to predict the most important food safety hazards and food products, with the aim of establishing a food safety monitoring program for herbs and spices. The prediction accuracy level, as assessed through model validation, exceeded 85%. The authors report that the BN model can be easily updated as new data becomes available, and it can be updated continuously by adding new variables to reflect new information.

Neural network

A NN model (Geng et al., 2017, 2019; Pham et al., 2005; Wang et al., 2017; Zhang et al., 2018) is based on a directed graph model with edges and nodes. The nodes correspond to neurons, and edges correspond to links between nodes. As input, each neuron receives the weighted sum of the output of the neurons connected to its entry edges. All neurons join together to carry out complex computations through communication links (Shalev-Shwartz & Ben-David, 2014). The output value of variables (nodes) for a new instance can be predicted according to the nonlinear combination of the values of several input variables and intermediary layers. NN, a supervised model for both regression and classification problems, is capable of dealing with incomplete datasets. It is characterized by the property of fault tolerance (i.e., corruption of one or more cells of NN does not prevent it from generating output). The NN model is regarded as a "black box," meaning that it is difficult to explain how and why it arrives at a given output (Chan et al., 2001; Paliwal & Kumar, 2009; Pan et al., 2008; Poddar et al., 2018). Geng et al. (2017) propose an analytic hierarchy process integrated extreme learning machine (AHP-ELM) aimed at building a prediction and optimization model for food safety inspection. An ELM is one type of NN and, for that study, the number of nodes in the input layer, output layer, and hidden layers was set at 11, 3, and 20, respectively. The proposed model is used to analyze food safety inspection data with complex, discrete, high-dimensional, and nonlinear properties. The accuracy and training time are verified using randomly selected 10% unused data. The average relative generalization error (0.5%) is nearly 20 times faster than the traditional artificial neural network (ANN) approach, with training time being 468 ms (nearly 10 times faster than the ANN approach). Zhang et al. (2018) report on an exploration of an ELM model to predict food safety risks in dairy products. The model is validated using the unused half of the same dataset, and the results reveal a network prediction accuracy level of 86% for the ELM network.

Support vector machine

A SVM model is constructed by assigning new examples to one category or the other by searching for "large margin" (i.e., distance to the closest data belonging to a class) separators. In the SVM, a training dataset is divided into two sides, separated by a half-space (hyperplane), with a large margin. The SVM is thus a nonprobabilistic binary linear classifier, with the better hyperplane having the lower functional margin; such greater margins are associated with lower levels of classification error (Cortes & Vapnik, 1995). The SVM uses direct decision functions that were originally designed for binary classification, although some researchers have since proposed an extension to multiclass classification (Duan & Keerthi, 2005). Given that restricting the model algorithm to generate a large margin separator can result in low sample complexity, the SVM model works well in high-dimensional problems (Shalev-Shwartz. & Ben-David., 2014). To obtain the best classification results, however, several key parameters of the SVM model must be set correctly, and this is not easy (Abe, 2005; Anguita et al., 2010; Pan et al., 2008; Weston & Watkins, 1999). Ma and et al. (2016) apply a parallel SVM model to explore a model of risk assessment for dairy production. The study is based on several data sources, including analytical data relating to dairy products, including the concentration of related factors (e.g., protein, sodium). Model prediction accuracy was as high as 90%.

Decision tree

A DT is a tree-like structure composed of leaves, branches, and internal nodes. Each leaf node represents a class label, with each branch representing the relationship of attribution and each internal node representing a "test" of an attribute. The classification rules are represented by the paths from the root to the leaf (Shalev-Shwartz & Ben-David, 2014). A DT is a supervised model for both regression and classification problems, and it can be easily understood. Although it yields the most optimal solution, it does not necessarily yield the globally optimal solution. The tree structure may become highly complex when training with complex datasets. Wu et al. (2019) use agricultural vegetable planting data to construct a DT model to early identify vegetable disease, thereby enhancing the quality and safety of crops. The results indicate a high level of accuracy for the DT model: 98.8%. An RF is an ensemble learning method on the basis of DT classifiers. An RF constructs a multitude of DT on various subsamples of the dataset in model training, and output the class that is the average prediction of the individual trees. A RF aims to improve the predictive accuracy of DT and control over-fitting.

Clustering and principal component analyses

Clustering and principal component analyses are both unsupervised ML techniques (Géron, 2019) and they are also traditional statistical methods. Because they have been widely discussed in the traditional statistical field, this review will not discuss them in detail.

3.3.3 | ML algorithms validation

In ML, model validation is referred to as the process in which a trained model is evaluated using a test dataset, which is a separate dataset that is not used to train the model (Alpaydin, 2010). Model validation includes internal and external validation, which can be interpreted into model reproducibility and model transportability (Altman & Royston, 2000). Internal validation is able to represent the model's reproducibility by running the model across unused data from the same target population. External validation is able to represent the model transportability by running the model across unused data from different but related populations. External validation is also able to represent reproducibility when the training data and test data have a very similar case mix. For internal validation, model performance was evaluated across test dataset from the whole dataset. Various methods can be applied, including random subsampling, k-fold cross-validation, and bootstrapping. Random subsampling involves sampling a training set and a test (i.e., validation) set independently, which is equivalent to partitioning the dataset randomly into two sections (such as 80/20). In k-fold cross-validation, the training set is divided into k subsets (folds). The ML model is trained on the other $k - 1$ folds (except the kth fold), after which the validation (i.e., the error of its output) is estimated using the k-fold. This process is repeated k times, with k being changed each time. The average of the validation accuracies indicates the accuracy of the model validation (Shalev-Shwartz & Ben-David, 2014). The researcher should be careful in order to avoid possible data leakage, which refers to a problem where knowledge of the test data is leaked into the training set, or knowledge from the future is leaked to the past. This can result in an incorrect and/or unrealistic estimate of model performance (Kuhn & Johnson, 2019). Most of the selected articles apply internal validation, that is, cross-validation (Balamurugan et al., 2019) or random subsampling validation (Geng et al., 2017; Sun et al., 2013; Wang et al., 2017; Zhang et al., 2018). In these studies, unused data from the whole dataset are used to validate the model performance. In external validation, model performance is evaluated across test data from different but related data sources, for example, temporal (e.g., different time range) to geographical (e.g., different region) related. Both Liu et al. (2018) and Ma et al. (2016) validated their model using unused data collected in a new year.

In addition to evaluating the generalization capacity of the ML model, the validation process also distinguishes ML models from statistical models. Although statistical models serve primarily to make inferences, ML models provide predictions and classifications. The boundary between statistical and ML approaches is not clear (Bzdok et al., 2018). Nevertheless, the inclusion of the ML model validation step as a selection criterion made it possible to exclude statistical models (e.g., Bayes inference) from our references.

3.4 | Application classification: Food safety hazard type of the relevant publications

3.4.1 | Specific food safety hazard(s)

Food safety hazards refer to all hazards that may make food injurious to the health of the consumer. They include: (1) Biological hazards, such as bacteria, viruses, parasites, and insects amongst others, (2) Chemical hazards, such as natural toxins, heavy metals, food additives, pesticides, and processing-induced chemicals among others, and (3) Physical/extraneous material hazards such as glass, plastic, and metal fragments (Lawley et al., 2012).

Biological hazards

Selected studies mainly focus on the bacteria and parasites classification and identification (Adem & Közkurt, 2019; Wasikowska et al., 2018), bacteria source attribution (Lupolova et al., 2017; Munck et al., 2020; Zhang et al., 2019) and managing the presence of bacteria by controlling the food storage process (Kuzuoka et al., 2020), classification of various types of crop insects (Ayan et al., 2020; Bisgin et al., 2018), and bacteria growth (Li et al., 2013; Qin et al., 2018). Munck et al. (2020) use LogitBoost algorithm to predict the origin of domestic human salmonellosis cases in Denmark. The most important source was pigs produced in Denmark (53%), followed by imported pigs (16%), imported broilers (6%), imported ducks (2%), and layers produced in Denmark (2%). Esser et al. (2015) summarize ML models, such as BN and NN, that have been applied to model microbial growth and activity, and they provide examples and applications in the context of food safety. Ayan et al. (2020) use seven different pretrained used convolutional NN (VGG-16, VGG-19, ResNet-50, Inception-V3, Xception, MobileNet, and SqueezeNet) to identify insect species to help reduce the yield loss in crops. Early identification can facilitate the necessary precautions for farmers. Estelles-Lopez et al. (2017) use ML models to predict the microorganisms, such as *Brochothrix thermosphacta*, Enterobacteriaceae, and pseudomonads, that cause meat spoilage. Some studies related to ML application on microbial growth and dynamics, mostly published before 2010, have been reviewed by Esser et al. (2015). Spectroscopy-based methods are mainly used for creating the data for analyzing biological hazards, whereas NN, SVM, BN, and RF are the most frequently used ML algorithms for modeling.

Chemical hazards

Studies mainly focus on the identification and detection of toxins (Chakraborty et al., 2021; Liang, Huang et al., 2020), pesticide residues (Gui et al., 2019; Mohite et al., 2017; Nie et al., 2021), and food additives (Šojić et al., 2019), as well as the estimation or prediction of the presence of heavy metals (Petrea et al., 2020; Yu et al., 2018). Nie et al. (2021) use deep learning combining with a terahertz imaging method to identify and visualize multiple benzimidazole pesticide residues on toona sinensis leaves. Chakraborty et al. (2021) use the KNN method to make classifications and predictions of aflatoxin B_1 concentrations in maize kernels. Petrea et al. (2020) use the RF method to determine the heavy metals concentration in turbot muscle and liver tissues. Similar to biological hazards, spectroscopy-based methods and computer vision are mainly used for creating the data for analyzing chemical hazards, whereas NN, SVM, and BN are the most frequently used ML algorithms for modeling.

Physical hazards

Studies mainly focus on the identification of abnormal cases (Lucas Pascual et al., 2020) and foreign objects (Rong et al., 2019). Lucas Pascual et al. (2020) use an NN to classify four possible pocket cases of olive: normal, empty, incorrectly de-stoned olives at any angles, and anomalous cases (foreign elements such as leaves, stones, small branches). Rong et al. (2019) use convolutional NN on walnut images to detect different foreign objects (e.g., packing material, leaf debris, dust, paper, metal, and/or plastic scraps). Again, image-based methods are mainly used for creating the data for analyzing physical hazards, and NN is the most frequently used ML algorithm for modeling.

3.4.2 | Food safety hazards in general

Food may be contaminated by a variety of safety hazards at the same time. Prediction of the combined presence of food safety hazards could help risk managers to focus on either the major food safety hazards or on the main factors contributing to the occurrence, in addition to controlling hazards at an earlier stage. In the relevant studies, food safety prediction is explored in two ways: one focusing on general food safety hazards given direct information on the food safety hazards such as from food safety monitoring records, and the other one predicting food safety events given information indirectly related to food safety events such as complaints and reports from consumers.

Prediction of general food safety hazards

The majority of the relevant articles focuses on general (combining multiple categories) food safety hazards using a BN model (Bouzembrak & Marvin, 2019; Liu et al., 2018; Marvin, Bouzembrak, Hendriksen et al., 2017), NN model (Geng et al., 2019; Geng et al., 2017; Zhang et al., 2018), SVM model (Ma et al., 2016), or DT model (Wu et al., 2019), mostly using historical food safety data from laboratory analyses (monitoring results).

Bouzembrak and Marvin (2019) present a BN approach using agricultural, climatic, and economic factors as input variables to predict the occurrence of food safety hazards in vegetables and fruits. The authors report that the methodology could help risk managers to identify the most important influential factors, as well as interrelationships between these factors and the presence of food safety hazards. Geng et al. (2017) propose an NN model using data from food safety inspections to analyze and predict food safety hazards in sterilized milk for the purpose of early warning. The results indicate that food inspection data could be used for predictive modeling, thereby providing tools for early warning for food safety. This approach could help risk managers to provide the baselines for scientific guidance, thereby promoting food safety and quality improvement. The BN model developed by Marvin, Bouzembrak, Hendriksen, et al. (2017) can be used to predict the biological effects and hazardous potential effects of metal nanomaterials and metal oxide nanomaterials, with the aim of supporting risk assessments for human health. The proposed model is capable of ranking nanomaterials according to two properties—hazard potential and biological effects—and evaluating the factors contributing to these two effects. Bouzembrak et al. (2018) apply a BN model to predict which types of food safety hazards occur in herb and spice products imported to the Netherlands, as well as which herb and spice products should be prioritized for monitoring at each stage of the supply chain (i.e., consumers, market, border inspection points, and suppliers). According to their results, at the stage of border inspection, food safety managers should focus on products, mainly chili peppers, curry, and curry leaves, imported from India. At the market stage, food safety managers should focus on nutmeg, chili peppers, and paprika imported from Thailand and India. The results reported by Bouzembrak et al. (2018) could thus guide governmental and industrial food safety inspectors in performing risk-based inspections.

Food safety events

Food safety events can be predicted and monitored by exploring information related to food safety from websites and other online media, emails, and other reports. This information can be used by ML algorithms for the classification, identification, and forecasting of food safety events. Relevant studies mainly focus on risk assessment (Song et al., 2020), classification of food safety events (Barbosa et al., 2019; Goldberg et al., 2020; Magalhães et al., 2020; Maharana et al., 2019), and the design of food safety warning systems (Chang et al., 2020).

Goldberg et al. (2020) use text mining and supervised ML to rapidly screen online media for reports on food safety hazards. Magalhães et al. (2019) use a text mining technique to textual data extracted from daily basis reports and complaints from consumers. Then they use Naive Bayes and SVM Classifiers to analyze the content of reports and complaints so as to determine whether the responsible entity is the Economic and Food Safety Authority. Chang et al. (2020) built an automated alarm system for the safety of edible oil by using electronic receipts.

3.4.3 | Prediction of food fraud

Application of ML on food fraud mainly focus on the prediction of general food fraud (Bouzembrak & Marvin, 2016; Marvin et al., 2016), classification of different quality levels of one food product (Dong et al., 2012; Vo et al., 2020; Zhang et al., 2014), and identification of added material to food (Laga & Sarno, 2020; Lim et al., 2016; Mithun et al., 2018).

Some studies apply the BN approach (Bouzembrak & Marvin, 2019; Laga & Sarno, 2020; Marvin et al., 2016), using data integrated from open access data and/or other data beyond the context of food safety to predict the occurrence of food fraud and to identify factors leading to food fraud activities. Activities involving food fraud—such as the adulteration of food with non-food-grade materials (e.g., dioxin-containing oils and Sudan dyes)—are increasingly posing a threat to food safety and raising consumer concerns (Spink & Moyer, 2011). Factors that could have a direct or indirect influence on the occurrence of food fraud incidents include climate, demographics, and the economy (Marvin et al., 2016). In one study, Marvin et al. (2016) apply a BN model to analyze all relevant driving factors related to food fraud incidents. Their results could help risk managers to identify the most important factors influencing food fraud, thereby strengthening their ability to promote the management, mitigation, and prevention of food fraud and the risks associated with it. The BN model developed by Bouzembrak and Marvin (2016), based on notifications of adulteration/fraud, can make predictions concerning the types of food fraud that could be expected to occur for specific imported products for which the country of origin and product category are known. The results could facilitate targeted enforcement activities by the government and food industries aimed at controlling food fraud. Mithun et al. (2018) use deep learning (NN) to classify naturally and artificially ripened bananas using spectral data. Artificially ripened bananas can be potentially ripened using carcinogens such as calcium carbide. Adulterated milk powder may have added melamine, a cheap nitrogen-rich substance that may be added purposely to increase the protein content and thus profits. Laga and Sarno (2020) use SVM, naive bayes, and RF to distinguish pure beef and mixed beef by analyzing beef features, such as temperature, strain, and humidity, by using electronic nose data. Lim et al. (2020) use deep learning to discriminative 10 different plant oil types from each other by analyzing fatty acid patterns of edible oils.

3.4.4 | Traceability

Traceability refers to the ability to trace and follow food, feed, and ingredients through all stages of food supply chain from production to processing and market distribution (European Commission, 2002). Information related to the food/feed and food/feed business operators can be gathered from a traceability system and analyzed to facilitate the monitoring of the supply chain (Balamurugan et al., 2019). Studies mainly focus on traceability and monitoring general food safety hazards in food supply chains (Alfian, Syafrudin, Farooq, et al., 2020; Alfian, Syafrudin, Fitriyani, et al., 2020; Balamurugan et al., 2019; Wang & Liu, 2019), as well as traceability based on animal features, which can trace the original source, uphold food safety standards, and ensure consumer confidence (Bennion et al., 2019; Ibáñez, 2015; Song et al., 2019; Tharwat et al., 2014).

Balamurugan et al. (2019) report on the development of a Bayes classifier for monitoring any irregular food condition (e.g., contaminated food needed to be recalled) throughout the entire food supply chain—from the producer to the consumer—based on internet-of-things (IoT) data. Their results can be used to prioritize food monitoring in order to ensure high food quality. Wang et al. (2017) propose an NN model for building a food traceability system to generate timely evaluations of food quality along the supply chain. Also, it can be used for forward tracing, while providing consumers with reliable information on the evaluation of food products. Sun et al. (2013) establish a fuzzy BN model to analyze data related to food safety extracted from a traceability system, in order to arrive at a direct indication for possible high risks in specific steps of the food production process. Two aspects, including the degree of microbial contamination in food and the content of poisonous and harmful substances in food, are identified as reflecting the food safety level. The model has been used to help food safety managers to make precrisis diagnoses and safety warnings, as well as to define liability issues throughout the food supply chain. Bennion et al. (2019) use RF model to classify and trace element fingerprinting data of blue mussel shells and soft tissues to reveal the harvest locations, and thus to identify possible contaminated produce. Song et al. (2019) use dynamic inlier selection to register pig skin images and apply convolutional NN to extract the features of pig skin and accurately trace pigs, so as to prevent pigs from carrying viruses that may be harmful to the liver and kidneys of consumers.

3.5 | Type of data

Data are fundamental to ML model analysis. Data used in the selected articles can be divided into two main categories: structured data and unstructured data. Structured data refer to data that are highly organized, usually come in the form of letters and numbers stored in tables or databases. Unstructured data refer to data that are not structured in a predefined format. It comes with a diversity of formats, usually a range of native formats, for example, imagery files or text files.

3.5.1 | Unstructured data

The relevant studies in this category mainly use image data (Adem & Közkurt, 2019; Kodors et al., 2020; Patsekin et al., 2019; Song et al., 2019; Vo et al., 2020), sensor data (mainly from spectroscopy and electronic noses) (Liang, Sun et al., 2020; Liu et al., 2020; Mithun et al., 2018; Tsakanikas et al., 2020; Weng et al., 2020), and text data derived from online media, emails, and reports (Mao et al., 2018; Vo et al., 2020). The most frequently used sources of unstructured data related to food safety have been reviewed recently (Jin et al., 2020; Zhou et al., 2019). The reader is referred to these two reviews for detailed information.

3.5.2 | Structured data

Structured data used in the relevant studies mainly refer to existing historical data, defined here as data gathered over a period of time and stored in a database/dataset, often from multiple rather than from a single study. The application of existing historical data in ML models can reduce the number of experiments, which require expensive and time-consuming operations and trained, specialized personnel (Chin et al., 2007). Structured data used in the selected studies were categorized into food safety monitoring data, open access data, expert knowledge, and other data.

Food safety monitoring data

Food safety monitoring data have been used in the development of ML models for predicting food safety hazards. Such data are based on results from laboratory tests, which provide detailed information on the presence/absence or concentration of hazards in food products. The information used (e.g., hazard concentration, product type, and/or compliance with legislation) is essential for the predictive modeling of the presence of hazards in food. In most cases, these data were not obtained from open data sources, but from public or private organizations, and some of these data were either not available or available only after obtaining permission.

As shown in Table 1, food safety monitoring data can be obtained from institutions that provide food inspection services (e.g., supervision and inspection departments, national food safety monitoring systems, and national institutes for public health). For example, Wageningen Food Safety Research (WFSR) is a unique knowledge institution in the Netherlands, with a focus on food and feed safety, which also functions as an international and European reference laboratory. Liu et al. (2018) use data collected on food safety hazards related to concentrations of the mycotoxin DON in wheat. Input variables gathered from this data source for purposes of predictive modeling include related mycotoxin and wheat-related data, such as country of origin, product category, sample collection, analysis date, hazard concentration, and compliance with legislation. These input variables have been used to develop a BN model for predicting the presence of the mycotoxin DON in wheat.

In another study, Geng et al. (2017) use data from laboratory analyses relating to food safety, as extracted from a quality supervision system (i.e., the repository of the Chinese inspection and supervision department). These data include data from the daily food safety inspections in the period from 2010 to 2014, as obtained from the Analysis and Testing Institute of one province in China. The model input variables consist of 11 important inspection indicators: arsenic, copper, lead, fenitrothion, hexachlorocyclohexane, cypermethrin, acephate, dichlorodiphenyltrichloroethane, *Escherichia coli*, total numbers of the colony, and the coliform group. These input variables have been used to develop a model to predict the food safety risk of dairy products.

Open access data

Open data sources on food safety have been applied to the prediction of aspects relating to one or more specific food safety hazards or the occurrence of fraud incidents. In most cases, these data are generated from historic information about food safety cases and food trade information. This information is usually easy to access, given that some of it should be known by the public. Usually, the type of data that can be used for modeling depends on the research question and the experience of experts.

As shown in Table 1, most open access sources of food safety data provide data relating to the food safety cases or food safety notifications published by the government or a food safety authority, for example, by the Food Protection and Defense Institute in the United States and the European Union's Rapid Alert System for Food and Feed (RASFF). The RASFF collects notifications on food safety incidents and instances in which legal limits have been exceeded when risks related to public health are detected in the food supply chain. The system enables efficient information sharing between the European Member States. The RASFF portal is an interactive, open access online database,[4] which provides the public with information about the most recent notifications, as well as other notifications issued in the past (RASFF, 2020). Marvin et al. (2016) use data on 1393 food fraud cases, as retrieved from the RASFF portal and several other databases. The input variables gathered from these data sources include food product category, food fraud incident date, type of food fraud, profitability level of the fraud, corruption level of the control country, and the food safety level of the origin country. These input variables have been applied to models for predicting the product categories with the highest probability of fraud. In another study, Bouzembrak et al. (2018)

[4] It is now closed since beginning of the year 2021.

TABLE 1 Data type and data source

Data type		Data description	Organization	Link/source
Food safety monitoring data	Analytical result	Hazard-related data from laboratory test (e.g., date of analysis, product category, product name, hazard concentration, laboratory equipment).	Food safety research institution (e.g., Wageningen Food Safety Research [WFSR])	Nonpublic
	Daily inspection and monitoring data	Inspection or monitoring data of overall food safety level (e.g., date of inspection, name of inspection item, inspection result, inspection standard).	Monitoring and inspection institutions (e.g., Chinese quality supervision system, Dutch National Institute for Public Health and the Environment [RIVM])	Nonpublic
Open access data	Food fraud cases	Data related to adulteration incidents in food products (e.g., food fraud incident year/month, product name, corruption level in the control country, food safety level in the origin country).	Institution with public food fraud information (e.g., Food Protection and Defense Institute [FDPI])	https://incidents.foodprotection.io/about
	Food safety case notifications	Data related to food safety notifications (e.g., date of notification, notifying country, classification, notification type, action taken, distribution status, product, substance/hazard).	Institution with public food-safety information (e.g., Rapid Alert System for Food and Feed [RASFF])	http://ema.foodshield.org/
Expert knowledge	Food chain information from traceability system	Food supply chain information quantified by expert knowledge (e.g., product inspection level, packing conditions, condition of transport).	Institution or company providing traceability or other information in food supply chain (e.g., Bureau of Quality) Supervision in a certain city in China, Shunxin Agriculture pork-producing company	Nonpublic
Other data	Economic information	Data related to economic information (e.g., product price, product trade volume).	Institution or company providing economic information (e.g., Eurostat)	https://ec.europa.eu/eurostat/en/home
	Climate information	Data related to climate information (e.g., temperature, humidity, precipitation).	Institution providing economic information (e.g., Royal Netherlands Meteorological Institute website)	http://www.knmi.nl/nederland-nu/klimatologie/daggegevens
	Clinic information	Data related to clinical information (e.g., age, gender, career, symptoms exhibited, home location, duration of disease).	Institution providing or gathering clinical information (e.g., China National Center for Food Safety Risk Assessment [CFSA])	Nonpublic

use food safety data extracted from the RASFF and Eurostat. Input variables for the model include the food safety hazard, the hazard category, the food product, product category, notifying country, origin country, notification type, trade volume, checkpoint, control point, and the compliance legislation. These variables are used as input into the model to predict the hazard category with the highest probability to occur.

IoT systems can provide important data related to food safety. This type of data includes information for tracking, tracing, sensing, and monitoring food products throughout the supply chain (Bouzembrak et al., 2019). An IoT system interrelates many devices and technologies to provide unique identifiers for physical objects, allowing physical objects to form an interconnected network without requiring interaction between humans or between a human and a PC. These devices and technologies (including radiofrequency identification technology, laser scanners, infrared sensors, information sensors, and global positioning systems) are able to collect various types of information (e.g., with regard to chemistry, biology, light, sound, heat, electricity, location, or mechanics) for food products in the supply chain. Balamurugan et al. (2019) use data from IoT systems for Bayes classifier modeling to build a traceability system for the food supply chain, which facilitates decision-making concerning the quality of food products. This system provides tracing and monitoring functions across various stages in the food supply chain (e.g., production, processing, warehousing, distribution, retail, and the end customer). Data used for modeling are collected from barcodes, sensors, RFID, and wireless network technology.

Banerjee et al. (2020) propose an IoT-enabled monitoring system, which can be deployed in remote areas to provide services to farmers with storage facilities to reduce food losses and increase food safety. This framework monitors warehouse parameters such as CO, humidity, motion, temperature, smoke, and vibration to reflect grain quality and safety.

Expert knowledge

Food safety data generated by experts are used primarily for traceability and monitoring food safety risks in the food supply chain. Although expert knowledge provides the opportunity to apply qualitative data for modeling, the quality of the data depends largely on the expertise of experts.

In the selected articles, most of the food safety data evaluated by experts consist of data provided by food safety institutions or food producing companies that offer information on the food chain. These data usually need to be interpreted with expert knowledge due to the lack of standardizing communication protocols.

The data sources used include the Bureau of Quality Supervision (Guangzhou, China) and a pork production company (Table 1). Wang et al. (2017) extract data related to the pork supply chain from one large pork company. The supply chain investigated in that study consists of the feed supplier, the farmer, the slaughterhouse, the wholesaler, the retailer, and the consumer. Supply chain information relates to raw materials, production, distribution, sales, and consumers. This information indicates the most important factors influencing the quality of the pork at each step in the supply chain. These factors are analyzed and evaluated by expert knowledge using a discrete scale ranging from 1 to 5. The results from these evaluation scales serve as input variables for the ML model, which is intended to predict the final pork quality grade.

In another study, Sun et al. (2013) use data relating to information on the food supply chain extracted from the traceability system of the Bureau of Quality Supervision in Guangzhou. Data include the conditions of transport, packing conditions, product inspection, and raw materials inspection. These model input variables are transformed into numerical values based on expert knowledge, and they are subsequently used in the ML model to predict the food safety risk level.

Other data

Data related to food safety from other fields have been applied largely to predicting aspects relating to one or more specific food safety hazards, the probability of fraud, and the outbreak of foodborne disease. Other data are usually ignored by modelers within the domain of food safety. Nevertheless, several authors have concluded that the major demographic, economic, and climate changes are having direct and indirect effects on food safety. These types of data can be taken into account in order to facilitate the management, mitigation, and prevention of risks associated with food safety (Bouzembrak & Marvin, 2019; Liu et al., 2018). Data relating to food safety from other fields are sometimes easy to access and could offer a variety of variables for modeling aimed at decision-making.

Other data sources used in the selected articles include the Royal Netherlands Meteorological Institute (KNMI), China National Center for Food Safety Risk Assessment (CFSA), Economically Motivated Adulteration (EMA), and Eurostat. Liu et al. (2018) use weather data extracted from the KNMI database for predictive food safety modeling, including hourly temperature, relative humidity, and rainfall, per geographical grid. Model input variables are calculated from these (raw) input data, for instance, the number of hours during which humidity is higher than 80%. These weather-related model input variables were subsequently combined with other input variables, such as the mycotoxin DON concentration obtained from laboratory testing, and agronomic variables, such as soil type, wheat cultivar, and the frequency of application of fungicides. All of these input variables are used to develop a BN model to predict the distribution probabilities for the class of mycotoxin DON (low, medium, and high) in wheat.

Another study is based on the Economically Motivated Adulteration (EMA) incident database, which provides information on recent and past EMA records, along with relevant information about EMA. Marvin et al. (2016) use data extracted from EMA and 14 other sources, both from inside and outside the context of food safety, to develop a ML model to predict food fraud. In addition to information on food fraud cases, model input variables include the product price, product demand increase, gross domestic product (GDP) of the origin country, product country of origin, annual trade volume, presence of a legal system for food in the origin country, political risk index of the origin country, and the Corruption Perception Index of the origin country. Those model input variables are used to predict the product category with the highest probability of fraud.

Eurostat, a statistical office of the European Union, provides reliable, high-quality, and objective statistics at the European level, thereby enabling comparisons of various situations between regions and/or countries. The Eurostat database includes general and regional statistics related to population, social, economic, and financial conditions. Bouzembrak et al. (2018) use economic data (on trade volume) extracted from Eurostat as one of the data sources for predicting the most important food safety hazards in herbs and spices.

3.6 | Future applications

This study has shown many promising applications of ML application in the context of food safety monitoring and prediction. However, the proposed studies mostly used one ML model for making food safety predictions. A few studies made comparisons among several ML models on the same dataset. Making comparisons among MLs could improve the opportunity of obtaining a better result of prediction. In addition, some studies used data from only one data source. The combination of several data sources to generate a larger dataset could increase the performance of modeling. More variables generated by data sources beyond the food safety field (which may influence food safety such as climate for mycotoxin) for modeling may also improve the model performance.

The comparison between MLs and the combination of more data sources could be taken into account for future ML applications in food safety. These two aspects had been identified by some included studies and other articles, and each aspect will be discussed below.

3.6.1 | ML model

The comparison between MLs researched in the context of food safety monitoring and prediction was investigated in several studies. Liu et al. (2018) compared the BN model to an empirical model and a mechanistic model. Their results showed that the BN model is easier to implement with incomplete input data. Geng et al. (2017) compared their proposed model (AHP-ELM) to backpropagation (BP) NN and radial basis function NN model to validate the effectiveness and robustness of the AHP-ELM. Their results showed that the performance of AHP-ELM model was the best. Laga and Sarno (2020) use *k*-NN, SVM, Naive Bayes, and RF model combining with electronic nose to classify the pure beef or mixed beef (combining beef and pork). RF results in the highest accuracy for classification. Zhang et al. (2018) compared their proposed model (Extreme learning machine) to BP NN and SVM model. The AHP-ELM network prediction accuracy was 86%, whereas the BP model and SVM model prediction accuracy was 78% and 83.2%, respectively. The model comparisons in these studies are able to either deal with the different types of data available or improve the opportunity of obtaining better prediction results.

Of the four basic ML models (applied in selected studies) discussed, NN, SVM, and BN are the ML algorithms that have been used most frequently within the context of monitoring and predicting food safety. Compared to other ML models, the BN's structure is easier to understand, and it more easily allows for the inclusion of expert knowledge. It appears to be a promising method for analyzing structured data within the context of food safety monitoring and prediction. This finding is in line with Marvin et al. (2016), who demonstrate that BN can be used as a holistic approach within the context of food safety and that it is capable of dealing with data from a variety of drivers (e.g., economy, climate change, and human behavior) to predict future events of food safety risks. Deep learning (various types of NN) has been proven to be an advanced technology for unstructured data analysis (e.g., image and text data) with a large number of successful applications in food (Zhou et al., 2019).

When focusing on the aspect of the prediction result, model performance could be compared if all ML algorithms are suitable for the particular modeling goal. The one with the best performance can be selected by comparing predictive accuracy based on the validation results when the various models are applied to the same validation dataset. Within the context of monitoring and predicting food safety, the performance of ML models was quite high, as evidenced by the high model validation results. More comparisons between MLs could be investigated in further research.

ML software, such as Scikit Learn, Pytorch, and TensorFlow, which require programming knowledge, are available for researchers to use. Low-code platforms (such as PyCaret, Auto-ViML, H2O AutoML) and no-code platforms (such as Create ML, MakeML, Google Cloud Auto ML, Runway AI), requiring basic programming knowledge, provide solutions with limited functions but allow researchers to quickly apply simple ML models on food safety monitoring.

3.6.2 | Data

In the food safety monitoring and prediction field, data are the basis for modeling. The lack of public and reliable data is the major hurdle for applications of ML for food safety monitoring and predicting. This problem has been given attention by Marvin et al. (2017) and Jin et al. (2020) who reviewed big data in food safety. They provide promising data sources within the context of food safety, and state that more and more data become available in food safety research nowadays.

As for the data sources and input variables derived from the included articles in this study, more similar data sources could be found in other countries from comparable institutions. For example, data on mycotoxin DON concentration obtained from the aforementioned data sources have been used in ML modeling to predict the probability of mycotoxin DON levels in wheat (Liu et al., 2018). Similar data related to other hazards and/or other products (e.g., the mycotoxin aflatoxin in corn) could be applied for modeling in the same way.

Other online data sources might contain or generate information relevant to food safety that could also be explored for use in ML modeling. Marvin et al. (2017) mention the food safety platform "FOSCOLLAB," which provides integration of various sources from multiple sectors, including animal, agriculture, food, public health, and economic indicators (WHO, 2015a). In addition, the Global Environment Monitoring System (GEMS) database contains important information on the properties of chemicals, growth conditions of microorganisms, and weather reports, which can be used to predict the presence of certain hazards (WHO, 2015b).

Besides online databases, other techniques (such as IoT, social media, smartphones, and satellite imagery) can be applied to provide data related to food safety. Bouzembrak et al. (2019) reviewed the IoT application in the food supply chain, which shows that the use of IoT can provide an enormous source of information related to food supply chain. The majority of information related to food safety that is measured by IoT refers to humidity, temperature, and geographical location (GPS). The information obtained from the communicated technologies (most frequently used in IoT were Internet, wireless sensor networks [WSN], and radiofrequency identification [RFID]) can provide more input variables for modeling and thus improve the traceability and monitoring in the food supply chain. Social media platforms such as YouTube, Twitter, and Facebook can be used to collect food safety-related information such as related to foodborne disease, food safety event discussions, or online questionnaires (Soon, 2020). The smartphone can be used to collect food safety data because it is usually applied for conducting food quality assessment, food safety hazard monitoring, and food inspection (Silva & Rocha, 2020). Satellite imagery can be used to collect imagery data related to agricultural product monitoring, such as crop growth and harvest (Mateus et al., 2019).

3.7 | Limitations of the search method

This paper followed the methodology of a systematic review, and did not include a meta-analysis. The search was restricted to references published between January 1, 2011 and April 1, 2021. Indeed, the most recent publications—published after April 1, 2021—are thus not included. But we believe the included publications capture the most up-to-date ML applications within the current field of interest. Because this review covered peer-reviewed research articles published in English, some articles related to the research question but written in other languages, such as Chinese (e.g., several articles published in 陈夏威 et al., 2019), were not included. The restriction to articles written in English was adopted in light of the fact that English is accepted as the universal language in science. By following the methodology of a systematic review, we did not read full texts in the screening step (b), because the aim of this step was to exclude all nonrelevant references and keep the relevant and possibly relevant references, and because of the large amount (1162) of the initial references. Only published peer-reviewed primary research articles from journals with an ISI impact factor were included in our review in order to reflect the scientific trend of ML applications for the monitoring and prediction of food safety. In this review, we critically evaluated the strengths and weaknesses of these studies. We found, for example, from all ML applications, BN was frequently used for modeling because its model structure is easy to understand and allows for easy incorporation of expert knowledge. We also provided recommendations for future studies, such as (a) comparing different MLs is useful for obtaining better prediction results, and (b) cross-validation and external validation are useful for validating model robustness. Our review focused in detail on ML application using structured data in the food safety domain. We only shortly mentioned ML application on unstructured data because unstructured data have been reviewed recently in a detailed way by several other review papers, and we have referred the readers to these review papers for more detail. Predefined search strings were set for the reference search. These search strings related to ML models probably did not cover all possible ML models, given the breadth and frequent updating of ML models (based on the basic ML models). The most commonly used ML models within the context of food safety were retrieved and discussed in the current review. The discussion could be used as an introduction to the topic and to provide insight for further investigation on other applications of ML models within this context.

4 | CONCLUSION

This study identifies and evaluates ML models for the monitoring and prediction of food safety. A systematic literature search yielded 114 relevant studies, 75% of which had been published in the last 5 years. The use of ML models within the context of food safety monitoring and prediction is thus still in its early stage but increasing rapidly. The predictive accuracy of the retrieved studies is high, indicating that ML models offer a promising method with regard to the monitoring and prediction of food safety. In the various ML models applied in the 114 studies, BN is the most frequently used algorithm for analyzing structured data, as its model structure is easy to understand and allows for easy incorporation of expert knowledge. NN is the main algorithm for analyzing unstructured data, as it can more easily handle image data and text data. The suggestions for data sources and input variables identified in this study suggest several avenues for future studies applying ML models for the monitoring and prediction of food safety.

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AUTHOR CONTRIBUTIONS

X. Wang Data curation-lead, writing-original draft-Lead; Y. Bouzembrak Writing-review and editing-equal; A. G. H. M Oude Lansink writing-review and editing-equal; HJ van der Fels-Klerx writing-review and editing-equal.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

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