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Machine learning and food inspection: use of Bayesian Network modeling to support official controls in the food industries

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Abstract

This study aims to develop a machine learning model capable of predicting the type of non-compliance (NC) most likely to be detected by competent authorities during official control of food establishments based on their structural, product, and management characteristics. A Bayesian Network (BN) model was developed using data from 145 NCs detected by the Local Health Authority of Messina during 588 official controls performed on 101 approved food establishments between 2018 and 2021. The NCs were classified into 10 distinct categories based on the requirement not met: i) structural and equipment conditions; ii) water supply; iii) fight against pests; iv) hygiene of staff and processing; v) cleaning and sanitizing conditions; vi) raw materials, semi-finished and finished products; vii) labeling; viii) traceability; ix) hazard analysis and critical control points (HACCP); and x) microbiological criteria according to Regulation (EC) 2005/2073. The model was constructed by associating the number and type of NC with the criteria and corresponding evaluations established by the Veterinary Services for each food establishment risk categorization according to Annex 2 of the *Intesa Stato-Regioni* CSR 212/2016. In detail, 8 different criteria were considered: i) date of construction or renovation; ii) general maintenance conditions; iii) marketing area; iv) food category; v) product intended use; vi) professionalism of management; vii) hygienic-sanitary training of employees; and viii) HACCP self-control plan. The BN model was implemented using the Hugin Lite software, considering the NC type as the parent node and the 8 different criteria as the child nodes. The implemented model allowed the prediction of the most probable type of NCs by inputting the evaluations of each risk categorization criterion for a given food establishment into the child nodes. A total of 25 NCs detected in 10 food establishments during 2024 were used to validate the model. The validation cases were not included in the learning dataset. The model correctly predicted the occurrence of 19 NCs (76%), while 6 NCs (24%) were not predicted, and 3 NCs (12%) were rightly predicted as the most probable ones. Although further efforts are needed to implement the model with a greater amount of data, this study highlights the potential of a BN-based approach as a valuable tool for competent authorities in organizing and performing official controls from a new technological and sustainable perspective.

Key words: artificial intelligence, AI, food control, neural network, naïve Bayes.

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Introduction

Regulation (EU) 2017/625 (“Regulation” from here on) is a legal framework established by the European Union concerning official controls on food and feed (European Parliament and Council of the European Union, 2017). Adopted on March 15, 2017, this Regulation became applicable on April 14, 2019, replacing the previous Regulation (EC) No. 882/2004 (European Parliament and Council of the European Union, 2004a). The primary goal of this legislation is to ensure a high level of food safety and consumer protection throughout the European Union, and it represents a further evolution of European legislation aiming at the development of increasingly sophisticated food safety control systems. The main pillars of the Regulation are: i) the enforcement of the integrations of controls; ii) the improvement of control plans; iii) the high attention to import controls; iv) the introduction of data management through the use of modern technologies and information-sharing systems such as electronic documentation, data exchange between member states, and the development of digital tools for risk assessment; v) the augmented attention for fraud prevention. These aspects are strengthened by a “risk-based approach” that represents a thread of the entire Regulation. This involves identifying and assessing potential risks associated with food and feed businesses and products. Resources are then allocated in proportion to these risks to ensure a targeted and efficient control system. Particularly, according to the Preamble n. 32 of the Regulation, “the frequency of official controls should be established by the competent authorities having regard to the need to adjust the control effort to the risk and to the level of compliance expected in the different situations, including the possible violations of the Union agri-food chain legislation perpetrated through fraudulent or deceptive practices. Accordingly, the likelihood of non-compliance (NC) with all the areas of the Union agri-food chain legislation which fall within the scope of this Regulation should be taken into account where adjusting the control efforts”.

These concepts represent an important evolution in the approach to food official control, not only because they link the control intensity to the risk level but also because they induce the consideration of the "expected level of compliance" or the "likelihood of NC" concerning the organization and realization of official controls. In the last decade, several studies have approached the theme of the risk categorization of food companies to assess the expected level of compliance with one or more requirements (European Regulations, Retailer standards, *etc*). Jacxsens *et al.* (2011) described, for example, some quantitative tools for the performance assessment and improvement of food safety management systems. An interesting approach to NC prediction is described by Marvin *et al.* (2016) and Bouzembrak and Marvin (2016), who use the Bayesian Network (BN) modeling to predict the likelihood of occurrence of food fraud. Particularly, these studies have used the BN to show possible links between food fraud cases retrieved from the Rapid Alert System for Food and Feed (RASFF) (EU) and or Economically Motivated Adulteration (EMA) (USA) databases and features of these cases provided by both the records themselves and additional data obtained from other sources. The obtained results suggest a potential application of these techniques to contribute to "adjust the (official) control effort to the risk and to the level of compliance expected in the different situations", according to the above-reported Preamble n. 32 of the Regulation. Moreover, as reported in several parts of the Regulation, for example, Article 9, "competent authorities shall perform official controls on all operators regularly, on a risk basis and with appropriate frequency". This implies a risk categorization of food establishments that allows the Local Competent Authorities to plan their official controls according to the risk evaluated for each food producer. In Italy, the risk categorization of food establishments is carried out according to the guidelines of the *Intesa Stato-Regioni* CSR 212/2016 (Ministero della Salute Italiana, 2016). In detail, this categorization considers 6 categories and 11 evaluation criteria as reported in Table 1. A score is established for each criterion; the sum of each score produces a value for each corresponding category, and its weighted sum provides the risk score of the food establishment [Food Plant Risk Score (FPRS)]. The FPRS is commonly yearly updated and used to plan the annual official control activities (inspection and auditing) in terms of frequency and intensity based on the assigned risk score.

This study repurposes risk categorization data to enhance compliance with regulatory requirements and improve official control effectiveness through an innovative technological approach. Specifically, risk categorization data were analyzed alongside official control results conducted by the competent authorities to explore potential correlations between NC occurrence and the characteristics of food establishments. On this background, the study aims to develop a BN model capable of predicting the type of NC that competent authorities are most likely to detect during official control of food establishments based on their risk categorization data.

Materials and Methods

Data collection

For the purposes of this study, the results of the official controls conducted between 01/01/2018 and 31/12/2021 by the Medical and Veterinary Services of the Provincial Health Authority of Messina (competent authority) were considered. Data were extracted from the management system provided to the competent authority, including only controls carried out at food establishments approved in accordance with Regulation (EC) 2004/853 (European Parliament and Council of the European Union, 2004b). NCs were classified into 10 distinct categories based on the specific regulatory requirement that were not met; in detail: i) structural and equipment conditions; ii) water supply; iii) fight against pests; iv) hygiene of staff and processing; v) cleaning and sanitizing conditions; vi) raw materials, semi-finished and finished products; vii) labeling; viii) traceability; ix) hazard analysis and critical control points (HACCP); and x) microbiological criteria according to Regulation (EC) 2005/2073 (Commission of the European Communities, 2005). For each food establishment where at least 1 NC was detected, the risk categorization assigned according to guidelines of the *Intesa Stato-Regioni* CSR 212/2016 (Ministero

Table 1. Categories and criteria for risk categorization of food establishments in Italy according to guidelines of the Intesa Stato-Regioni CSR 212/2016.

Category	Criterion		Evaluation			
Characteristics of the food establishment	1	Date of construction or renovation	New	Recent	Fairly recent	Dated
	2	General maintenance conditions	Good	Fair	Poor	Insufficient
Production body	3	Establishment size	Family	Artisan	Medium industrial	Large industrial
	4	Marketing area	Local	Regional	National	Extra EU
Products	5	Food category	Stabilized	Pasteurized or not support bacterial growth	Support bacterial growth	Complex processes that require refrigeration storage
	6	Product intended use	-	To cook	Ready to eat	Categories at risk
Production Hygiene	7	Professionalism of management	High	Fair	Low	Insufficient
	8	Hygienic-sanitary training of employees	High	Fair	Low	Insufficient
HACCP self-control plan	9	Self-control plan	Complete	Adequate	To be integrated	Inadequate
	10	Application level	Applied	Minor deficiencies	Major deficiencies	Not applied
Historical data	11	Previous non-compliance	Not significant	Not significant repeated	Severe and isolated	Severe and repeated

HACCP, hazard analysis and critical control points; EU, European Union.

della Salute Italiana, 2016) was also extracted considering only 8 of the 11 available criteria; in detail: i) date of construction or renovation; ii) general maintenance conditions; iii) marketing area; iv) food category; v) product intended use; vi) professionalism of management; vii) hygienic-sanitary training of employees; and viii) HACCP self-control plan.

Implementation of the Bayesian Network model

According to Ancione *et al.* (2020), BN is a probabilistic graphical model that can be applicable to a wide range of purposes, such as monitoring, classification, clustering, and prediction. Structured as a directed acyclic graph, it comprises nodes connected by directed arrows, representing, respectively, a set of random variables ($X = \{A1, A2 \ldots AN\}$) and the dependencies among them. If variables are discrete (as in the present study), they consist of a finite set of mutually exclusive states that explain the specific and potential conditions of each variable.

If there is an arrow from node Ai to node Af, node Ai is the parent node while Af is the child node. The variable Ai, along with its parent pa(Ai), represents the conditional probability distribution $P(Ai \mid pa(Ai))$. Conditional probability tables (CPTs) are assigned to each node, reflecting the type and strength of causal relationships between parent and child nodes (Zarei *et al.*, 2019). BN provides a unique joint probability distribution, $P(X) = P(A1, A2, \ldots AN)$, by combining the CPTs of all variables using the following formula [Eq. 1]:

$$P(X) = \prod_{i=1}^{n} P(Ai \mid pa(Ai)) \qquad \text{[Eq. 1]}$$

In the present study, the CPTs of the BN model were constructed by relating the number and type of NCs with the criteria and respective evaluations of the risk categorizations of the considered food establishments.

Figure 1 graphically represents the BN model herein implemented, which consisted of a parent node (*i.e.*, "NC type"), directly linked to 8 child nodes consisting of the risk categorization criteria reported above (see paragraph "Data collection"). The distinct states of each node are reported in Table 2. The implemented model enabled the prediction of the most likely type of NCs by inserting the evaluations (*i.e.*, the states) of each risk categorization criterion of the considered food establishment as input data in the child nodes. The machine learning technique "expectation maximization algorithm" was used to construct the BN model and to compute CPTs between variables. The learning step was performed using the learning algorithm of the Hugin Lite software (v.9.4) (http://www.hugin.com/).

Bayesian Network validation

Cross-validation is a widely used statistical method to evaluate a model's predictive performance on new data. It involves training the model on multiple subsets of the available data and evaluating its predictive accuracy on each corresponding hold-out subset (Ancione *et al.*, 2020). In this regard, the goodness of the BN model was evaluated by testing its ability to predict NCs that had not been used in the learning dataset. In detail, 25 NCs detected during 10 official controls carried out in 10 food establishments in 2024 were used to validate the BN model. The attributes of each criterion of the food establishment risk categorization were used as input data in the child nodes evaluating the probability percentages of the different states in the parent node (*i.e.*, the probability percentage of the different NC categories reported in the paragraph "Data collection"). The results were divided into "predicted" when NC was predicted at least as possible and "not predicted" when the percentage probability of the NC occurring was 0%. In order to evaluate the performance of the model, it was also assessed whether the predicted NCs were identified as the actually "most probable ones".

Results and Discussion

Nowadays, new technological approaches for carrying out official controls in the food industries have become increasingly needed to address the demands and challenges of global agri-food markets (Gbashi and Njobeh, 2024). The dynamic evolution of

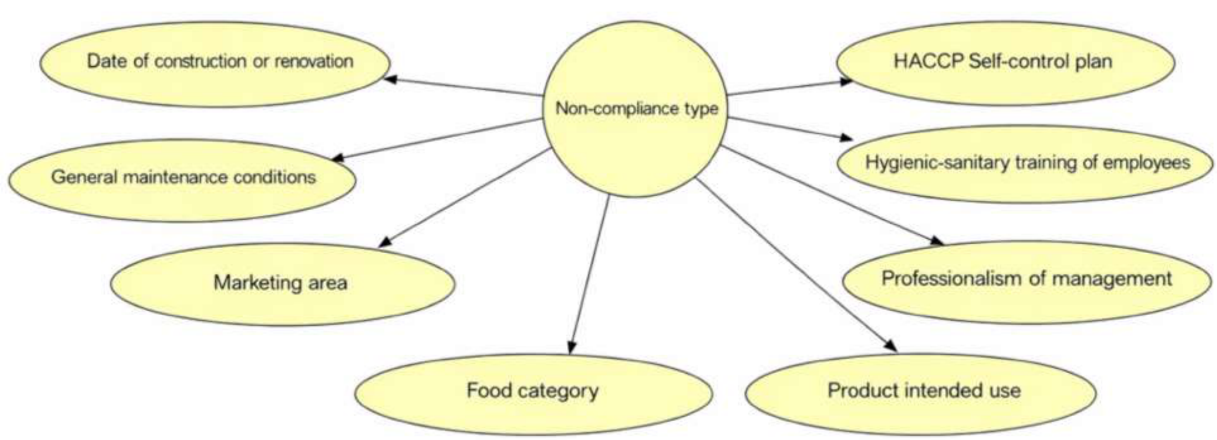

Figure 1. Graphical representation of the Bayesian Network implemented in the present study using Hugin Lite software (v.9.4). HACCP, hazard analysis and critical control points.

global supply chains, increased consumer expectations for food quality and safety, and the need for efficient compliance with complex regulatory requirements entail innovative solutions (Liu *et al.*, 2023). In this perspective, machine learning modeling could be a suitable alternative to improve the efficiency of monitoring systems in terms of reliability and cost-effectiveness, promoting a safer and more sustainable approach to food inspection. The BN model herein implemented has highlighted the potential of the machine learning-based approach, although still preliminary and with some potentially relevant limitations related to data acquisition. Overall, the data of the NCs considered in the present study for the implementation of the BN were summarized in Table 3. In detail, for constructing the learning dataset, a total of 588 official controls carried out on 101 food establishments, consisting of 14 different activity categories, were considered. Autonomous cold stores were the most frequently inspected food establishment category (26.02%), followed by meat product plants (18.88%) and dairy product plants (11.05%).

A total of 145 NCs were detected in 46 (45.54%) food establishments, and 65 (11.05%) official controls were used for implementing the BN. HACCP (24.64%), structural and equipment conditions (20.29%), and fight against pests (15.22%) represented the most frequently detected types of NC.

Milk collection plants were the food establishment category with the highest percentage of official control, with at least 1 NC (33.3%), followed by autonomous repackaging establishments (22.2%) and live bivalve mollusk purification establishments (15.4%). Considering only official control with at least 1 NC, egg and egg product packing center was the food establishment category with the highest number of NCs (n. 5 NC/official control), followed by food wholesale establishments, autonomous repackaging establishment, and live bivalve mollusk purification center (n. 4 NC/official control). As regards the model validation, among the 25 NCs considered, HACCP (28%) was the most represented type,

Table 2. Nodes and related sets of mutually exclusive states of the Bayesian network implemented in the present study.

Node	Set of mutually exclusive states
Non-compliance type	Structural and equipment conditions, water supply, fight against pests, hygiene of staff and processing, cleaning and sanitizing conditions, raw materials, semi-finished and finished products, labelling, traceability, HACCP, microbiological criteria according to Regulation (EC) 2005/2073
Date of construction or renovation	New, recent, fairly recent, dated
General maintenance conditions	Good, fair, poor, insufficient
Marketing area	Local, regional, national, extra EU
Food category	Stabilized, pasteurized or not support bacterial growth, complex processes that require refrigeration storage
Product intended use	To cook, rady to eat, categories at risk
Professionalism of management	High, fair, low, insufficient
Hygienic-sanitary training of employees	High, fair, low, insufficient
HACCP self-control plan	Complete and applied, adequate with minor deficiencies, to be integrated with major deficiencies, inadequate and not applied

HACCP, hazard analysis and critical control points; EU, European Union.

Table 3. Data relating to non-compliance used in the present study for the implementation of the Bayesian network.

Establishment type	n. establishments	n. controls	n. NC	n. controls with NC	% n. control with NC / n. controls	n. NC / n. control with NC
Freezer vessel	1	1	0	0	0.00	0.00
Wholesale trader	2	14	8	2	14.29	4.00
Autonomous cold store	30	153	25	12	7.84	2.08
Repackaging plant	1	9	8	2	22.22	4.00
Slaughterhouse	5	53	7	3	5.66	2.33
Cutting plant	4	53	7	5	9.43	1.40
Meat product plant	24	111	29	17	15.32	1.71
Purification centre	1	13	8	2	15.38	4.00
Dispatch centre	6	60	18	9	15.00	2.00
Fishery product plant	5	29	9	3	10.34	3.00
Milk collection centre	2	6	2	2	33.33	1.00
Dairy product plant	16	65	17	6	9.23	2.83
Cheese maturing centre	2	8	2	1	12.50	2.00
Egg packaging centre	2	13	5	1	7.69	5.00
Total	101	588	145	65	11.05	2.23

n, number; NC, non-compliance

followed by structural and equipment conditions (20%) and the fight against pests (15.22%). Regarding the performance of the model, a total of 19 NCs (76%) were correctly predicted, 6 NCs (24%) were not predicted, and only 3 NCs (12%) were predicted as the most probable ones. Mode calculation revealed that the NCs used for validation were most frequently predicted as the 3rd most probable.

The predictive performances of the model herein implemented are lower than those obtained in other similar studies. For example, the BN model developed by Bouzembrak and Marvin (2016) to predict food fraud by knowing the production country obtained a correct prediction of 80%. Similarly, Soon (2020) developed a BN model to predict food fraud obtaining a performance prediction of 85%. In this regard, a limited number of data used in the learning dataset could negatively affect the prediction performance of our model. In fact, it is well known how "big data" are needed for implementing reliable and efficient machine learning models (Zhou *et al*., 2017). The BN model herein implemented can be expanded and improved by incorporating other national and international data relating to official controls in the food industries, thus increasing the learning dataset and improving predictive performance. Further improvement could be achieved by finding possible relationships between variables, increasing the model complexity through a higher level of detail and knowledge.

Data quality and availability are critical determinants for the effective implementation of a machine learning model, as its performance is inherently dependent on the data integrity (Gong *et al.*, 2023). Biases embedded in training datasets can profoundly influence machine learning algorithms, potentially leading to unexpected and skewed outputs (Gbashi and Njobeh, 2024). In our case, data acquisition did not negatively influence the reliability of the model, as there was a single source of data supply. However, in the future perspective of improving the model with national and international data, the lack of standardization in the collection and interpretation of the official control results related to the flexibility of the legislation may negatively affect the implementation of a robust predictive model.

Conclusions

In the present study, we presented a new application of BN modelling to predict the type of NC in food establishments using data related to their structural, product, and management characteristics. Although further efforts are needed to implement the model with a greater amount of data, the present study has highlighted how machine learning could be a useful tool for organizing and performing official controls in a new technological and sustainable perspective.

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