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Artículos de Revisión

Support Vector Machines for Predicting the Level of Integration in Agri-Food Chains*

Máquinas de soporte vectorial en regresión para la predicción del nivel de integración en las cadenas agroalimentaria

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Douglas Andrés Verduga-Alcívar
Universidad Técnica de Manabí, Ecuador
ORCID: https://orcid.org/0000-0003-4984-0441

Emanuel Guillermo Muñoz-Grillo
Universidad Técnica de Manabí, Ecuador
ORCID: https://orcid.org/0000-0002-0997-0578

Erik Orozco-Crespo
Universidad Técnica de Manabí, Ecuador
ORCID: https://orcid.org/0000-0003-2811-6243

Teresita López-Joy
Universidad Tecnológica de la Habana, Cuba
ORCID: https://orcid.org/0000-0003-4579-9197

Ana Julia Acevedo-Urquiaga
Fundación Universitaria San Marcos, Perú
ORCID: https://orcid.org/0000-0001-7867-1590

Neyfe Sablón-Cossío [a]
Universidad Técnica de Manabí, Ecuador
nsabloncossio@gmail.com
ORCID: https://orcid.org/0000-0002-6691-0037

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Abstract:

Objective: The objective of this paper is derived from a theoretical analysis of the application of support vector machines to the design and management of agri-food chains. This analysis is conducted using an empirical approach to predict of the level of integration in agri-food chains by support vector machines.
Materials and Methods: The methodology designed and utilized to process the research results, which consists of the training of support vector machines, is employed to predict the level of integration in an agri-food chain. This type of predictive application appears in the reviewed literature on the integration of agri-food chains.
Results and Discussion: The analysis is performed by comparing the proposed method with a neural network technique. The research results focus on predicting the level of integration in agri-food chains using vector machines.
Conclusions: The study provides a support vector machine model that is applied to other case studies and therefore allows for the prediction of outcomes. The paper also compares two techniques that share the goal of prediction, as applied in different contexts
Keywords: supply chains, prediction, food and vectors.

Resumen:

Objetivo: El objetivo de este trabajo se deriva de un análisis teórico de la aplicación de las máquinas de vectores soporte al diseño y gestión de cadenas agroalimentarias. Este análisis se realiza mediante un enfoque empírico para predecir el nivel de integración en cadenas agroalimentarias mediante máquinas de vectores soporte.
Materiales y Métodos: La metodología diseñada y utilizada para procesar los resultados de la investigación, que consiste en el entrenamiento de máquinas de vectores soporte, se emplea para predecir el nivel de integración en una cadena agroalimentaria. Este tipo de aplicación predictiva aparece en la literatura revisada sobre integración de cadenas agroalimentarias.

Author notes

[a] Correspondence author: nsabloncossio@gmail.com

Resultados y Discusión: El análisis se realiza comparando el método propuesto con una técnica de redes neuronales. Los resultados de la investigación se centran en la predicción del nivel de integración de las cadenas agroalimentarias mediante máquinas vectoriales.
Conclusiones: El estudio proporciona un modelo de máquina de vectores soporte que se aplica a otros casos de estudio y, por tanto, permite predecir resultados. El documento también compara dos técnicas que comparten el objetivo de la predicción, aplicadas en contextos diferentes

Palabras clave: cadena de suministro, predicción, alimentos y vectores.

Introduction

Agri-food chain integration is currently a challenge because agri-food products are perishable and consumers are highly demanding. Food chains are a strategic area of permanent interest[1]. An agri-food chain should be understood as the processes that are carried out from supplies and raw materials to production and the reception of products by consumers. This chain includes the stakeholders, the stages, factors and costs of production, industrialization and the distribution of agricultural goods, covering both direct and indirect activities [2].

Agri-food chains comprise production, processing and logistics entities that are focused on obtaining products and services in the food industry. In general, a company or institution that is part of the agri-food chain itself acts as its coordinator, which must be supported by a legal framework [3]. In agri-food chains, the logistical problem lies in the coordination of supplies, from the inputs needed to secure the harvests as primary production to the processing technology, packaging, and inputs needed for industrial production (such as seasonings, additives, preservatives, binders, and cleaning products)[4].

Currently, chain integration is a key factor in enhancing the competitiveness of the chain and its stakeholders [5]. Chain integration is an indispensable element for achieving shared goals and high positioning. Consequently, studies of chain integration continue to be interesting, fundamental and necessary. An important characteristic of agri-food chains is the varied and combined demand for their final products, accompanied by various services. End and intermediate consumers are continuously influenced by various variables that determine the amounts to be produced in each link of the chain. Analyzing their behavior on the basis of mathematical models facilitates the planning of each entity or company and adjusts its production [5].

These elements, in addition to the traceability and agility necessary for products to last over time, often lead to the premature adoption of decisions. For this reason, it becomes necessary to use tools that enhance prediction, considering the variables and parameters that influence the management of each supply chain. As a result, the objective of this paper is to predict the level of integration in agri-food chains using support vector machines in three different contexts, namely, an agri-food chain of tomato sauce production in Cuba, an agri-food chain of chocolate bars and an agri-food chain of cow milk; the latter two are located in the Ecuadorian Amazon. The first chain is established in the context of extensive production in a centralized economy. The remaining two chains are established in the context of small farms linked to the achievement of greater production and sales volumes.

The importance of this research lies in its methodological contribution, as it results in a support vector machine model that can predict integration to facilitate decision-making in different contexts. There is also a social contribution, consisting of the possibility of making decisions in anticipation of the possible needs of consumers. The direct antecedent of this research is related to the prediction of chain integration in Muñoz et al. (2020), although neural networks are employed [6].

This document is structured as follows: Section 2 presents a theoretical analysis of the application of support vector machines to agri-food chains, including a general description of the countries where the integration model was applied (subject of study). Section 3 discusses the materials and methods employed to predict agri-food chain integration. The analysis results are shown in Section 4, while Section 5 presents the discussion and conclusions of the research.

Applications of Support Vector Regression Machines (SVR)

This section analyzes the applications of support vector regression machines in supply chains, with the objective of identifying the main gaps that made this study possible. Regarding the application of this technique to agri-food chains, 123 articles were found in the Scopus database covering the period from 2003 to 2020 (Table 1).

TABLE 1.
Analysis of issues related to support vector machines in chains

Themes	Percentaje	Authors
Optimization, algorithms and simulation	12.2	Liu et al [7], Wan et al [8], Chen [9], de Cos Juez et al [10], Shi [11], Zhang and Zhang [12], Tokgöz et al [13], Bocca and Rodrigues [14], Arnold et al [15], Asala et al [16], Bhosekar and Ierapetritou [17], Huo and Wang [18], Masna et al [19], Li and Roche [20]
Information management and technologies	15.45	Zhang et al [21], Wang and Chen [22], Zhan et al [23], Gultyaeva et al [24], Shetty et al [25], Yoo et al [26], Kamble et al [27], Lima et al [28], Wan et al [29], Weese et al [30], Uddin et al [31], Akhtar et al [32], Behera and Misra [33], dos Reis et al [34], Ma et al [35], Memon et al [36], Singh et al [37], Wei et al [38], Jan et al [39]
Integration	5.69	Li et al [40], Lei and Junfei [41], Li et al [42], Li et al [43], Carbonneau et al [44], Zhao and Xu [45], Zhang [46]
Demand forecast	20.33	Liu et al [7], Carbonneau et al [44], Lu and Zhang [47], Yue et al [48], Carbonneau et al [49], Shahrabi et al [50], Wu [51], Yue et al [52], Jaipuria and Mahapatra [53], Xie et al [54], Zhang et al [55], Ayyanathan and Kannammal [56], García et al [57], Vaitkus et al [58], Ayyanathan and Kannammal [59], Gamasaee et al [60], Sarhani and El Afia [61], Yue et al [62], Villegas et al [63], Kilimci et al [64], Tran et al [65], Abolghasemi et al [66], Liu and Huang [67]

Source: The Authors.

Of these studies, 5.69% focus on the application of support vector machines to the problem of integration in supply chains, which is the objective of this research. For example, [120-122] discuss the diagnosis and collaboration relations of stakeholders in the supply chain, while [123] addresses their joint performance. Although in recent years, studies have focused on forecasting demand, the studies of [124] also cover learning methods for the design of new integration strategies in the proposed forecast system, ensuring a significant improvement in the supply chain. Nevertheless, the study of integration continues to be an important aspect of decision-making in supply chains, mainly food and food byproduct chains.

Preliminary research works related to the subject of this study

Based on the applicability of support vector regression machines to different variables of the supply chain, an integration gap was identified. Then, the authors employed the methodology proposed by Sablón [4] to assess the level of integration. This algorithm is applied to supply chains of various countries, products and scopes (Figure 1).

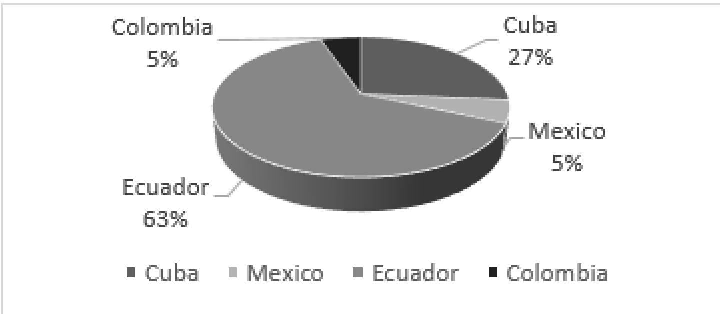

FIGURE 1.
Countries where the level of integration methodology is applied to agri-food chains
Source: This graph was created on the basis of the results and research articles by Sablón and his collaborators from 2013 to 2021.

Materials and methods

This section describes the integration calculation methodology as a traditional estimation model and the support vector regression techniques for integration prediction.

Methodology to calculate the level of integration

This methodology is explained in detail by Sablón et al. (2021) as a traditional estimation model. The following variables are calculated: strategy, information, planning, purchases, inventory, transportation and collaborative performance. They are disaggregated into items evaluated by using a 5-point Likert scale, which is an ordinal scale, in which 1 point corresponds to the lowest rating and 5 points corresponds to the highest rating.

On the basis of the chain integration level (IL), it is possible to identify the joint strategies and objectives of the agri-food chain under study. Consequently, the need arises to assess the prospects of this integration level to anticipate possible market changes, so it is proposed to make predictions by using support vector regression machines.

Methodology for the training of support vector regression machines

The authors use the support vector machine training methodology of [125] to predict the level of integration in agri-food chains. This methodology uses algorithms to create a support vector regression machine and determine its parameters.

Nonlinear Case

In the search for the general form of the regression function as a linear function, the following set is considered: $C = \{(x_1, y_1), \dots, (x_n, y_n)\}$, where $x_i \in \mathbb{R}^d$ and $y_i \in \mathbb{R}$. Thus, $\Phi\colon \mathbb{X} \to \mathcal{F}$ will be the function that establishes a correspondence between each input value x and a value in the feature space F, where F is a Hilbert space. This feature space can be high-dimensional or even infinite-dimensional. The function is expressed as follows (equation 1):

$$f(x) = \langle w, \Phi(x) \rangle + b \tag{1}$$

C = Soft margin cost parameter - (function used for training or as a training set)
x = Independent variables
w = Weight vector
$f(x)$ = Objective function
ϕ = feature function
b = KKT (Karush-Kuhn-Tucker) complementary conditions
The primal problem, in this case, does not depend directly on the examples of the set but on its images by

the given function ϕ (equation 2).

$$\begin{aligned} &\min \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{n}(\xi_i + \xi_i^*) \\ s.a \quad & y_i - \langle w, \phi(x_i)\rangle \leq \varepsilon + \xi_i \quad i = 1, \dots, n \\ & \langle w, \phi(x_i)\rangle - y_i \leq \varepsilon + \xi_i^* \quad i = 1, \dots, n \\ & \xi_i \geq 0, \ \xi_i^* \geq 0 \quad i = 1, \dots, n \end{aligned} \tag{2}$$

C = Soft margin cost parameter - (function used for training or as a training set)
ε = Margin parameter
x = Independent variables
y = Dependent variables
w = Weight vector
$f(x)$ = Objective function
$\xi_i,\ \xi_i^*$ = Dual variables
ϕ = Feature function

The complexity of this problem lies in the dimension in which the examples are located. After being transformed by the function ϕ, the examples could become very high-dimensional, which would greatly complicate providing a solution to the primal problem. Then, the associated dual problem is formulated as follows (equation 3):

$$\max -\frac{1}{2}\sum_{i,j=1}^{n}(\alpha_i-\alpha_i^*)\,(\alpha_i-\alpha_i^*)\langle\phi(x_i),\phi(x_j)\rangle-\varepsilon\sum_{i=1}^{n}(\alpha_i+\alpha_i^*)$$

$$+\sum_{i=1}^{n}y_i(\alpha_i-\alpha_i^*)$$

$$s.a \qquad \sum_{i=1}^{n}y_i(\alpha_i-\alpha_i^*)=0$$

$$\alpha_i,\alpha_i^* \ \in [0,C] \tag{3}$$

C = Soft margin cost parameter - (function used for training or as a training set)
ε = Margin parameter
α = Lagrange multipliers
x = Independent variables
y = Dependent variables
$\alpha_i,\ \alpha_i^*$ = Dual variables
ϕ = Feature function

Kernel trick

¿Could we solve this problem without explicitly recognizing the function ϕ? The answer is yes. After formulating the dual problem, it was observed that the objective function depends only on the inner product of the images of our examples. The kernel trick algorithm is widely employed in inner product calculation algorithms of the form $\langle\phi(x),\phi(x')\rangle$ in the feature $\mathcal{F}$ space [126].

The trick consists of the notion that, instead of calculating these inner products in $\mathcal{F}$, what is actually used for the calculation, due to its possible high dimensionality, is to define a kernel function, $K : X \times X \rightarrow \mathbb{R}$, which assigns a real value to each pair of input space elements X. That real value corresponds to the scalar product of the images of said elements in the new space $\mathcal{F}$

$$K(x,x') = \langle \phi(x), \phi(x') \rangle$$

K = Kernel

ϕ = Feature function

x, x' = Arguments

Where ϕ: → X to apply the kernel trick for this type of problem were [125].

The problem to be solved by applying the kernel trick. Once the kernel is set, it is used to solve the problem. (Equation 4):

$$\max -\frac{1}{2}\sum_{i,j=1}^{n}(\alpha_i-\alpha_i^*)(\alpha_i-\alpha_i^*)K(x_i,x_j)-\varepsilon\sum_{i=1}^{n}(\alpha_i+\alpha_i^*) + \sum_{i=1}^{n}y_i(\alpha_i-\alpha_i^*)$$

$$s.a \qquad \sum_{i=1}^{n}y_i(\alpha_i-\alpha_i^*)=0$$

$$\alpha_i, \alpha_i^* \in [0, C] \tag{4}$$

with the prediction function (equation 5):

$$f(x)=\sum_{i=1}^{n}(\alpha_i-\alpha_i^*)K(x_i,x)+b \tag{5}$$

ε = Margin parameter
α = Lagrange multipliers
x = Independent variables
y = Dependent variables

f(x) = Objective function

$\alpha_i,\ \alpha_i^*$ Dual variables

ϕ = Feature function

C = Soft margin cost parameter - (function used for training or as a training set)

$\mathcal{F}$=Hilbert space or feature space

b = KKT (Karush-Kuhn-Tucker) complementary conditions

K = Kernel

x_i,*x* = Arguments

Kernel function

An inner product in the feature space has an equivalent kernel in the input space:

[126] $K(x, z) = \langle \phi(x), \phi(x) \rangle$

The peculiarity of kernel functions leads to the definition of the function $K : X \times X \rightarrow \mathbb{R}$ as finitely positive semidefinite if it is symmetric, and the matrices composed of any finite set of space *X* will be positive semidefinite. This definition does not require that *X* be a vector space.

Theorem:: The function K： X ×X → R, may be either continuous or have a finite domain. It is broken down into (equation 6):

either continuous or have a finite domain. It is broken down into (equation 6):

$$K(x, z) = \langle \phi(x), \phi(x) \rangle \tag{6}$$

K = Kernel

ϕ = Feature function

x,z = Arguments with a given feature function φ in a Hilbert space $\mathcal{F}$ applied to the 0 arguments and followed by an evaluation of the inner product in $\mathcal{F}$ if and only if *K* is finitely positive semidefinite.

Given the function *K* that satisfies the previous condition, that is, that it is finitely positive semidefinite, the corresponding space $\mathcal{F}$ is referred to as the Hilbert space reproduced by the kernel [127]. (equation 7):

Kernel types Polynomial

$$K_d(x, x') = \sum_{s=0}^{d} \binom{d}{s} R^{d-s} \langle x, z \rangle^s \tag{7}$$

Gaussian Radial Basis Function

$$K(x,x') = \exp\left(-\gamma \|x - x'\|^2\right) \tag{8}$$

K = Kernel
x, x', z = Arguments
d = Kernel degree
s = Dimension of the original input space
R = Dimension
K = Kernel
x, x' = Arguments
γ = Shape parameter, which has three parameters. Optimal parameters (C, ε y γ) are not known.

Exponential Radial Basis Function

$$K(x,x') = exp\left(-\frac{\|x - x'\|}{2\sigma}\right) \tag{9}$$

K = Kernel
x, x' = Arguments
σ = Real Variable
γ = Shape parameter, which has three parameters. Optimal parameters (C, ε y γ) are not known (equation 10).

Multilayer or Sigmoid Perceptron

$$K(x,x') = tanh(\gamma\langle x - x'\rangle + R) \tag{10}$$

K = Kernel
x, x' = Arguments
σ = Real Variable
γ = Shape parameter, which has three parameters. Optimal parameters (C, ε y γ) are not known.

The application of the procedure described above is performed in the RStudio IDE (integrated development environment) program of Neuralnet. First, the integration level (IL) is calculated by the traditional method in three different contexts, and then, the results are predicted using support vector machines. Afterward, the results are compared. (equation 11).

Results

The support vector regression machine forecasting procedure is applied to the three chains under study, to identify the differences in the application for integration estimation.

Application 1: Agri-food chain of tomato sauce

The agri-food chain under study comprises six links and 22 stakeholders and is classified into the following entities: suppliers of inputs for agriculture and the industry; farmers grouped in cooperatives; food processing entities located in different territories; warehouses of the focal company and the aforementioned stakeholders; the tomato importer that acquires the products that cannot be supplied by the national industry; the focal company that in this case is also the commercial chain; the points of sale, which are the stores of the retail network; and the end customers. This is a national chain with an average level of collaboration. Input suppliers provide machinery and raw materials, and there is only one stakeholder within the study area. Tomato is the main raw material used for the production of tomato puree and its by-products, which poses a problem centered around 85% availability and 50% variety of the main product.

After identifying the chain stakeholders, the authors applied the checklist to evaluate the level of integration. Additionally, the value of applying the checklist was analysed in addition to the input and output variables. The real values and the estimates, accounting for 30% of the data used to test the model, which include negative estimators, constitute preliminary results whose ranges must be adjusted. The execution time of the learning algorithm of the support vector machines is 3 seconds. This result demonstrates the performance of the second in relation to time. The estimated results of the resulting variable (Table 2) show that the vector model makes better estimates of the input variables in the first layer.

To evaluate the support vector machine model, 30% of the data, which were not part of the machine training data, were utilized. The model was applied, and the values were estimated through the process explained above. The estimators were compared with the real values, and the Spearman correlation coefficient was calculated to establish that the data have similar values and are the closest to 1 or -1. Regarding correlation, the result for this chain is 0.04783165, which is low (Figure 2).

TABLE 2.
Results of the NI resulting variable of the tomato supply chain

	NI	Estimate
1	1.56	1.921101
2	1.70	1.883934
3	2.05	1.883934
4	1.35	1.949580
5	2.03	1.900514
6	1.41	2.302186
7	1.39	1.900514
8	2.01	2.116739
9	2.23	1.551517
10	2.30	1.866765
11	1.90	2.133586
12	1.50	2.004110
13	1.57	1.925563
14	2.11	2.031002
15	2.08	2.136756
16	2.10	2.084169
17	2.24	2.005655
18	2.41	2.191243
19	1.79	2.082107
20	2.20	2.272754
21	2.00	2.450961

Source: The Authors.

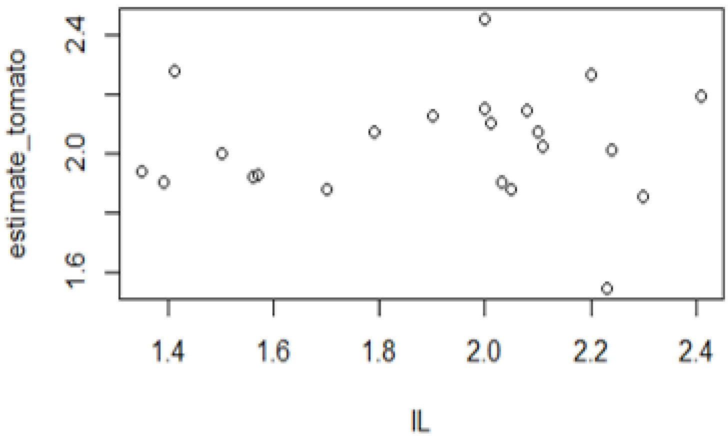

FIGURE 2.
Regression coefficient
Source: The Authors.

Application 2: Agri-food chain of chocolate bars

The chocolate chain of the Ecuadorian Amazon consists of five links, nine industries and four collection centers. This chain is centered around the production of chocolate bars of various concentrations, but the study was delimited to the geographical area of the Ecuadorian Amazon, which is where sowing, harvesting and gathering take place. Processing and sales do not occur in this region. The chain under study has a basic level of integration that demands research on logistics, product design, legal agreements between two stakeholders, certified suppliers, and industries that respect product brand and brand development.

The estimated results of the resulting variable are shown in Table 3. These estimators were compared with the actual values, and the Spearman correlation coefficient was calculated. Regarding correlation, the result for this chain is 0.85172292, which is high (Figure 3).

TABLE 3.
Results of the NI resulting variable of the chocolate supply chain

	NI	Estimate
1	1.914062	1.922385
2	1.000000	1.072532
3	2.414062	2.359897
4	2.000000	2.034138
5	1.906250	1.918023
6	1.000000	1.072532
7	2.179688	2.006879
8	1.000000	1.072532
9	3.648438	3.336079
10	2.000000	2.034138
11	1.523438	1.522865
12	1.700000	1.553335
13	1.835938	1.843293
14	1.000000	1.072532
15	1.843750	1.885860
16	1.000000	1.072532
17	2.710938	2.876941
18	1.000000	1.072532
19	1.367188	1.407894
20	2.000000	2.034138
21	2.000000	2.034138

Source: The Authors.

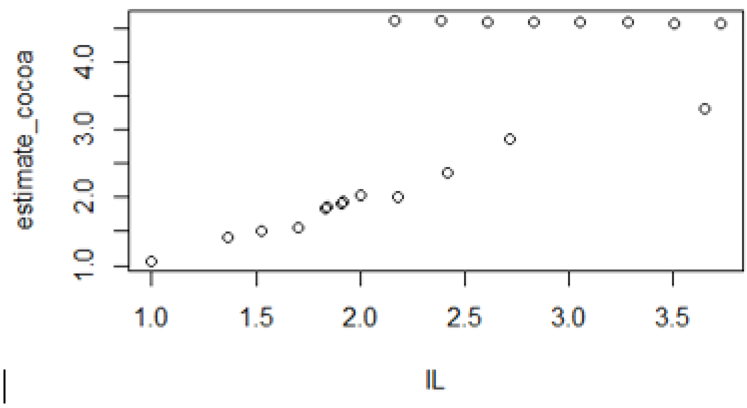

FIGURE 3.
Regression coefficient of the chocolate supply chain.
Source: The Authors.

Application 3: Agri-food chain of cow milk

The supply chain in Puyo city, which is located in the Pastaza province of the Ecuadorian Amazon region, comprises thirteen stakeholders grouped into four links: suppliers, producers, sellers and consumers (13 stakeholders). The level of integration is low, and the most deficient variable is the evaluation of stakeholder performance. In the chain under study, the stakeholders that show the greatest weaknesses are the livestock farmers and markets (sellers). The estimated results of the resulting variable are shown in Table 4. The estimators were compared with the real values, and the Spearman correlation coefficient was calculated. Regarding correlation, the result for this chain is 0.94989064, which is high (Figure 4).

TABLE 4.
Results of the NI resulting variable of the milk supply chain

	NI	Estimate
1	2.366460	2.924506
2	3.726708	4.574257
3	1.732919	2.642065
4	2.739130	3.104736
5	2.745342	3.006319
6	3.795031	4.330430
7	3.503106	4.580460
8	1.956522	2.867822
9	1.000000	1.093115
10	3.018634	3.238490
11	2.590062	3.077739

Source: The Authors.

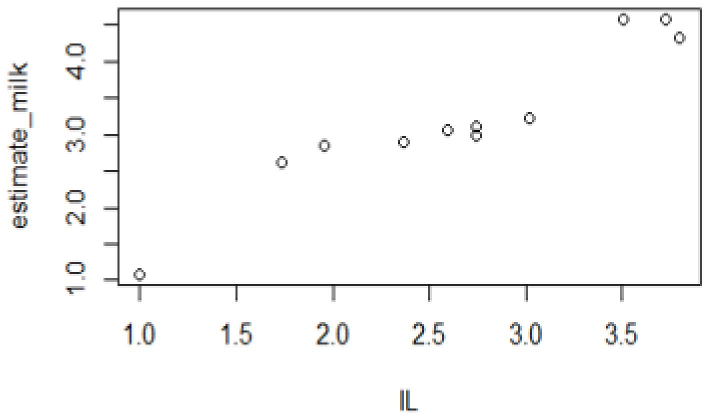

FIGURE 4.
Regression coefficient of the milk chain
Source: The Authors.

The results reveal that the tomato chain has a low correlation coefficient, and the proposed model is not good for prediction in this case (Table 5) due to the few values included in the study.

TABLE 5.
Correlation coefficient results.

Agri-food chains	Chocolate	Milk	Tomato
Spearman correlation coefficient in support vector machines	0.8500268	0.9514307	0.1413561

Source: The Authors.

Discussion

The study of integration in supply chains and its prediction were analysed in an article by Muñoz [6]. The difference between this article and the previously mentioned article lies in the use of a different technique for integration prediction. In the article by Muñoz, neural networks were applied, while in the previously mentioned article, support vector machines were utilized. In both cases, the proposed application was viable for solving the problem, as shown in Table 6.

TABLE 6.
Results of the correlation coefficients of the two methods

Agri-food chains	Cocoa	Milk	Tomato
Spearman correlation coefficient in support vector machines	0.8500268	0.9514307	0.1413561
Spearman correlation coefficient in neural networks	0.8867229	0.6533274	0.1455274

Source: The Authors.

The support vector regression machine (SVM) and neural network (NNET) models have a good predictive capacity when training the learning models. In the case of the chocolate bar chain, the NNET correlation coefficient was 0.8867229, while the SVM coefficient was calculated at 0.8500268. In this case, the NNET coefficient is better than that of the SVM. In the case of the milk chain, it was observed that the SVM correlation coefficient is 0.9814307, which is a strong positive correlation that is superior to the NNET correlation coefficient, which is 0.6533274. On the other hand, in the case of the tomato chain, the correlation coefficient results are not very good in either of the two models because few data records are available.

Irrespective of this finding, the results of both techniques were compared by using the Wilcoxon signed-rank test, which is a nonparametric test. As a result, the test statistic was 0.5476, and the null hypothesis was not rejected. There are no significant differences between the machine learning methods when comparing the integration estimates of the chains under study. The number of NI estimates in the analysed chains does not vary between the two prediction methods, namely, the support vector machines and neural networks, and a 95% confidence interval was applied for the mean of the estimates, according to the method (Figure 5).

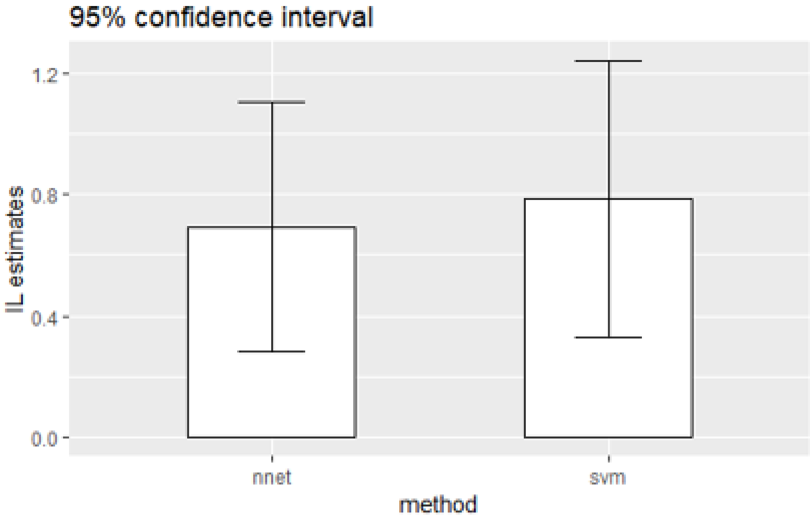

FIGURE 5.
Comparison of significant differences between support vector machines and neural networks for the prediction of chain integration
Source: The Authors.

It was observed that the 95% confidence intervals overlap, thus confirming that the methods do not exhibit significant differences.

Conclusions

In the current context, the techniques for the prediction of integration in agri-food chains are necessary for decision-making in different scenarios, considering the characteristics of the targeted products, namely, food and its byproducts. Therefore, this research was carried out using actual data for the application of an integration prediction checklist. The results demonstrated the predictive capacity of support vector machines in three agri-food chains in different contexts, in addition to the capacity to generate an SVR prediction model, with the correct kernel and hyperparameter configuration, and the achievement of greater accuracy than the standard multiple linear regression solution.

The study concluded that SVR calculation does not depend solely on the dimension of the input space. Therefore, it is suitable to solve a high-dimensional problem without having to address the curse of dimensionality, which proves its generalization. In addition to the configuration of parameters, the SVR model also depends on the training dataset, and there is no permanent solution for this task. This finding is specifically evidenced by the low Spearman correlation value in the cow milk chain. For future research, the authors propose to compare the results of applying support vector machines in different agri-food chains that may be of interest.

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Notes

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