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Application of neural networks in the prediction of the circular economy level in agri-food chains

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ABSTRACT

The objective of the work is to predict the level of circular economy in the agri-food chain through an empirical neural network approach. The research methodology includes the training of a neural network to predict the level of 128 circular economy in two agri-food chains. The novelty of this work lies in the possibility of defining in advance circular strategies based on the prediction of the level of circular economy. Historical data on the level of circular economy are compared with those predicted by neural networks. As a result, it is shown that if the weights of the circular economy level variables are not homogeneous, the procedure has a lower correlation value which, however, remains significant.

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1. Introduction

The Circular Economy (CE) has, in the last decade, motivated a different perspective of the economic model, from linear to circular consumption [1]. The CE is defined as an appealing alternative that aims to redefine what growth is, with an emphasis on societal benefits [2]. It involves divorcing economic activity from the consumption of finite resources and eliminating waste from the system, from design to consumption.

The objective of one part of the circular economy is to improve the use of resources throughout the entire life cycle of products by means of circular remanufacturing [3], [4]. This is supported by a transition to renewable energy sources. The circular model creates economic, natural, and social capital [5], and

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is based on three principles: eliminating waste and pollution by design, keeping products and materials in use, and regenerating natural systems [6].

The circular economy is, meanwhile, a concept that is understood to comprise actors in agri-food chains and its core 'the cycle from my supplier's supplier to my customer's customer'. Furthermore, the circular chain is an open system that allows resources to flow between chains as well as inside technological and natural material cycles [7]. It focuses on addressing pollution, manufacturing patterns and marketing, reducing the materials employed, and climate change [8]. This is because the adoption of circular models for the flow of goods, resources, and waste could allow the integrations between chain actors to reduce waste and harmful environmental influences in the chain [9], which applies to the agri-food chain.

The goal of this article is to use neural networks to forecast the level of the circular economy in shrimp and cheese agri-food chains. The significance of this research stems from its methodological contribution, which includes the development of a trained neural network capable of predicting the circular economy in order to make decisions and direct possible strategies. It also makes a social contribution that is framed in the possibilities of making anticipated decisions to carry out circularity in the chain processes.

Previous studies have employed neural networks to evaluate requests for the purchase of customer debt in banks in Peru [10]. Moreover, Muñoz et al. [11] applied neural networks in order to predict the level of integration in a supply chain. Furthermore, the work of Diéguez-Santana et al. [12] evaluated the circular economy by employing a systemic tool. These are all similar applications that use the same technique but for different objectives.

1.1 Applications of neural networks in the circular economy

The application of neural networks in the circular economy has been diverse and has employed different variables. Scientific texts related to the subject were searched for in the Scopus database using the terms "neural network". This made it possible to identify 75 documents related to this specific topic, which were published from 2010 to 2022. Of these, 54.6% allude to the use of this technique in some component that integrates the circular economy (Table 1).

The uses to which this technique was put in these studies were identified as: green energy, waste and recycling, products, biorefinery, sustainability, ecology and sustainability, decision models, supply chains and a general study of the circular economy variable. Of these, 29% refer to waste and recycling elements and 17% to sustainability, ecology and sustainability, Figure 1.

An analysis of the literature in question showed that only 3% of the studies are related to the work carried out herein, thus showing the usefulness of this application for the subject under study.

1.2 Preliminary research on the subject under consideration

According to the specialized literature reviewed, different approaches have been used to investigate the level of the circular economy in agri-food chains. However, the approach employed in this paper is the circular economy level assessment methodology of Diéguez-Santana et al. [12]; this is due to the tool is systemic when confronted with such a broad term.

Table 1. Applications of neural networks to the evaluation of components of the circular economy

Applications	Autor/ year	Reference
Energy	Bartie et al., 2021; Ding et al., 2022; Garg et al., 2022; Joshi et al., 2021; Li et al., 2021; Luo & Oyedele, 2021; Wen et al., 2021	[13]-[19]
Waste and recycling	Alhazmi et al., 2021; Alonso et al., 2021; Dashti et al., 2021; Facchini et al., 2021; Kazançoğlu et al., 2021; Khayyam et al., 2021; Lu et al., 2021; Matheri et al., 2021	[20]-[27]
Products	(Assunção et al., 2022; Basia et al., 2021; Lau Hiu Hoong et al., 2021; Sathiya Prabhakaran & Swaminathan Swaminathan, 2022; Sow et al., 2021	[28]-[32]
Biorefinery	Culaba et al., 2022; Sidiras et al., 2022	[33], [34]
Circular economy	Diéguez-Santana et al., 2021	[12]
Sustainability, ecology, sustainability	Gong et al., 2021; Gue et al., 2022; Kazançoğlu et al., 2021; Lee et al., 2021; Liu, 2021; Shabanpour et al., 2021	[27], [35]-[39]
Decision models	Culaba et al., 2022; Fetanat et al., 2021; Sidiras et al., 2022	[33], [34], [40]
Supply chain	Kazancoglu et al., 2021; Shabanpour et al., 2021	[36], [41]

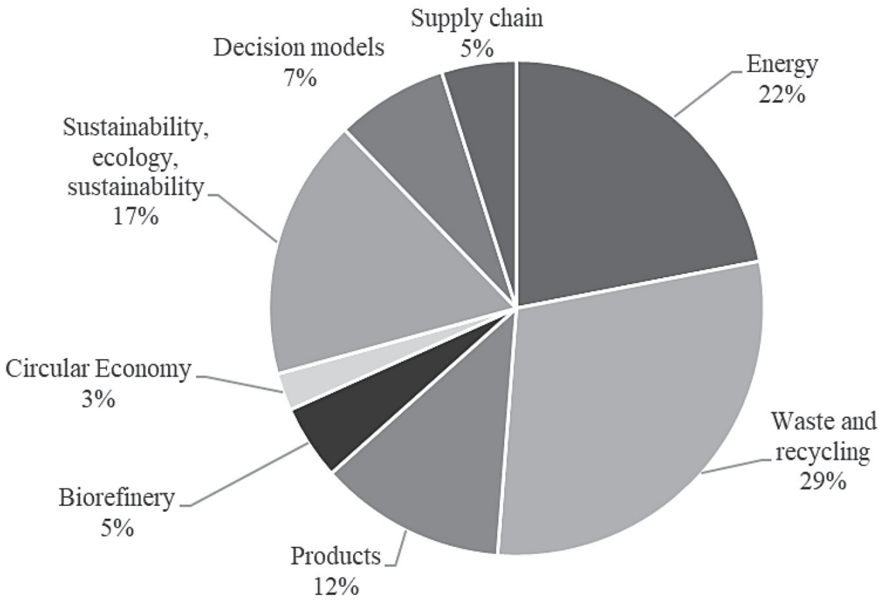

Figure 1. Analysis of the use of neural networks in circular economy in agri-food chains

This algorithm is used in agri-food chains of various products and scopes (Table 2).

2. Methodology

A neural network training methodology was used to forecast the level of circular economy in agri-food chains [10], [11]. The architectural algorithm and the supervised learning algorithm were employed in the building of a neural network in this methodology.

Both approaches were used in the setting of an agri-food chain in Ecuador. First, the standard method was used to determine the Circular Economy Level (CEL) for agri-food chains, and then this result was forecasted using neural networks. These two outcomes were associated, and the prediction error was calculated. This study was conducted for variables with varying and equal levels of relevance. These outcomes were then compared.

2.1 Calculation of the CEL

This process begins with the formation of each actor's working group. These groups are based on the staff's experience and the impact of their knowledge on decision-making. The Hierarchical Analytical Method is used to assign weight or relevance to each variable in the work group. A checklist of 91 elements from Diéguez-Santana [12]. was applied to each actor in the chain. Descriptive statistical research is used to assess it, in which the weight of each variable is multiplied by the findings of the relevant items. The factors are as follows: source or supply of materials (D1), design manufacturing (D3), economic circle (D4), distribution and sales (D5), consumption and use (D6), 4R (D7), remanufacturing (D8), and sustainability (D9). Each variable is composed of a series of factors, for a total of 91 elements in the Check List used to assess the level of circular economy (CEL).

Table 2. Studies of agri-food chains of various products and scopes

No.	Study objects	Application	Development
1	Coconut agri-food chain in Manabí, Ecuador	Product	Medium
2	Cheese agri-food chain in Chone, Ecuador	Product	Medium
3	Shrimp agri-food chain in Manabí, Ecuador	Product	Medium
4	Plantain agri-food chain in Manabí, Ecuador	Product	Medium
5	Cocoa agri-food chain in Manabí, Ecuador	Product	Medium
6	Organic cocoa agri-food chain of an association as a center, Ecuador	Product	Medium
7	Pitahaya farm, Palora, Ecuador	Product	Total
8	Coffee agri-food chain, Manabí, Ecuador	Product	Medium

Source: Prepared from the results and research papers of the Production and Services Group, Ecuador (2019 to 2022).

The following variables are used:

m: a nominal variable that identifies the supplier chain.

j: a nominal variable that identifies the supply chain company. m. (All of the variables in the checklist are measured at the corporate level.)

Ekj: ordinal variable assessed on a Likert scale of 1 to 5 (Very Low = 1, Low = 2, Medium = 3, High = 4, and Very High = 5), where k corresponds to the 91 checklist elements k = [1, 2... 91], sorted by dimension.

Dij: is a scale variable derived from the mean of the related Ek.

CEL: a scale variable that specifies the circular economy level of the supply chain m, as measured by the average CEL of all the enterprises j that comprise it, as calculated by equation 1

$$CEL = \frac{\sum_{j=1 \,\forall j \in m}^{n} CEL_j}{n} \qquad (1)$$

CELj: a scale variable that determines the level of circular economy for company j using equation 2:

$$CEL_j = \sum_{i=1}^{9} (w_i * D_{ij}) \qquad (2)$$

Wi: the exact weight assigned to each Di.

Based on the strategies defined by the Bocken's study [42] and the interpretation interval for the prediction of the circular economy level of the chain (CEL) obtained in each case [43], certain strategies are recommended. Table 3 shows the circular economy business strategies while Table 4 presents the recommendations to adapt these strategies according to the CEL. This proposal is not strictly mandatory, but is based on some success stories collected in the literature [44]-[47]. However, it is imperative for enterprises to discern their particular requirements and investigate the strategies that most effectively fit their needs during that particular period, as it is improb-

Table 3. Business model strategies to introducing CE into supply chains

Business model strategies	Initials	Definition
		Business model strategies for slowing loops
Access and performance model	A&P	Providing the capability or services to satisfy user needs without needing to own physical products
Extending product value	EPV	Exploiting residual value of products – from manufacture, to consumers, and then back to manufacturing – or collection of products between distinct business entities
Classic long-life model	CLLM	Business models focused on delivering long-product life, supported by design for durability and repair for instance
Encourage sufficiency	ES	Solutions that actively seek to reduce end-user consumption through principles such as durability, upgradability, service, warrantees and reparability and a non-consumerist approach to marketing and sales (e.g., no sales commissions)
		Business model strategies for closing loops
Extending resource value	ERV	Exploiting the residual value of resources: collection and sourcing of otherwise wasted" materials or resources to turn these into new forms of value
Industrial Symbiosis	IS	A process- orientated solution, concerned with using residual outputs from one process as feedstock for another process, which benefits from geographical proximity of businesses

Source:[42]

Table 4. Business model strategies recommendation from CEL evaluation

CEL: circular economy level		**Business model strategies for slowing loops**				**Business model strategies for closing loops**	
Very low	≤ 1,5	EPV					
Low	(1,6; 2,5)	EPV	A&P			IS	
Middle	(2,6; 3,5)	EPV	A&P	CLLM		IS	ERV
High	(3,6; 4,4)	EPV	A&P	CLLM	ES	IS	ERV
Very high	> 4,5	EPV	A&P	CLLM	ES	IS	ERV

Source: elaborated form [42]-[47]

able that any preexisting strategy would serve as a universally applicable solution.

3. Results

On the basis of the process built for the algorithm that compares errors, the approach for forecasting neural networks was used, with two specifications, namely when the weight is homogeneous and when it is heterogeneous.

3.1 Case study 1: Ecuadorian Chone cheese agri-food chain

The investigated chain contains six links and 81 actors. It is divided into three categories: veterinary supplies, primary producers, processors, wholesalers, vendors, and customers. The product is sold mostly in bulk but in large volumes throughout the country. This shows that the chain is national in scope.

There are three types of cheese: hard, semi-hard and soft, depending on its characteristics. The importance of this product lies in the fact that it is basic element of the Ecuadorian diet and is widely recognized by customers in this area. The waste produced by the chain is principally whey, which is almost always thrown away or used as livestock feed, despite its usefulness as human food.

After identifying the actors, the checklist for assessing the level of the circular economy was applied to them. Tables 5 and 6 describe the values of the checklist application and the analysis of the nine dimensions with heterogeneous and homogeneous weights, respectively. Each has nine input variables and one output variable.

The network's architecture, which comprised an input layer, was recognized. It had nine neurons for each covariate, ten neurons for the hidden layer, and one for the output layer because it was a prediction.

A random sample of 75% of the database was collected and used to train the neuron so that the data for each variable was sent to each input neuron. Each connection's weights and balances, as well as a balance, were obtained.

These were distinguished by the use of weights and balances ranging from 0 to 1, and the activation function was maintained. Each neuron in the neural network was subjected to this calculation. If the values acquired as a result of the activation function produced signals at extremely high or extremely low levels, this aided in determining the relevance of each neuron. To simplify the calculations, the first derivative of the function was employed, which increased the signal's forward propagation (importance of the variable). This was done in stages until all of the net-

Table 5. Input and response variables with heterogeneous weights

D1	D2	D3	D4	D5	D6	D7	D8	D9	CEL
1,2	1,11	1,2	1,8	1,3	1,1	1,4	1,25	1,7	1,41
1	1,11	1,2	2,2	1,8	1	1,3	1,23	1,7	1,6
1	1,11	1,2	1,9	1,5	1	1,3	1,67	1,7	1,47
1	1,11	1	2,8	1,3	1	1,2	1	1,7	1,56
1,1	1,11	1,2	1,9	1,4	1	1,2	1,25	2,4	1,42
1	1,11	1	2,7	1,6	1,1	1,1	2,31	1,6	1,71
1	1,11	1,2	1,9	1,3	1	1,2	1,23	1,7	1,38
1	1,11	1	2,3	1,3	1	1,2	1,63	1,7	1,47
1	1,11	1	1,8	1,3	1	1,1	1,25	1,7	1,33
1	1,11	1	1,8	1,2	1	1,1	1,23	1,7	1,28
1	1,19	1	1,7	1,5	1,1	1,1	1,25	1,6	1,35
1	1,11	1	1,8	1,3	1	1,2	1,25	1,7	1,33
1	1,11	1	1,6	1,2	1	1,1	1,25	1,6	1,26
1	1,11	1,2	1,4	1,2	1	1,1	1,63	1,7	1,27
1	1,11	1,2	1,8	1,1	1	1,3	1,25	1,6	1,32
1,8	1,62	2,5	2,2	1,8	1,1	1,2	1,67	2,5	1,92
1,2	1,11	1,2	2,2	1,5	1,2	1,3	1,67	1,7	1,56
1,3	1,11	1,2	1,9	1,5	1,1	1,4	1,25	2,5	1,48
1,2	1,11	1,2	1,9	1,5	1,2	1,3	1,67	1,7	1,5
1,2	1,11	1,2	1,9	1,5	1,2	1,3	1,67	1,7	1,49

Table 6. Input and response variables with homogeneous weights

D1	D2	D3	D4	D5	D6	D7	D8	D9	CEL
1,22	1,54	1,85	2,04	2,17	1,17	1,46	3,75	2,42	1,94
1,38	2,4	2,36	2,22	2,26	1,54	1,72	2,18	2,82	2,08
2,03	2,61	3,26	2,35	2,29	1,48	1,79	2,53	2,05	2,24
1,76	1,98	3,16	2,38	2,4	1,23	1,9	2,05	2,09	2,08
1,41	1,97	1,94	1,99	2,66	1,15	1,95	1,25	2,18	1,81
1,5	1,89	2,94	2,83	2,05	1,57	1,69	1,48	3,43	2,13
1,04	1,19	1,43	1,41	1,38	1,35	1,52	1,55	1,92	1,41
1,14	1,54	2,14	1,83	1,54	1,35	1,77	2	2,05	1,69
1,04	1,29	1,67	1,52	1,38	1,23	1,48	1,6	2,09	1,46
1,09	1,39	2	1,69	1,41	1,23	1,46	1,92	2,09	1,57
1,04	1,28	1,43	1,56	1,4	1,32	1,65	1,85	2,09	1,5
1,04	1,28	1,67	1,42	1,32	1,23	1,44	1,5	2,09	1,43
1,09	1,4	1,67	1,69	1,32	1,26	1,57	1,92	2,09	1,54
1,41	1,36	1,18	1,92	1,95	1,42	1,89	2,76	2,05	1,75
1,6	1,36	1,4	2,35	1,64	1,06	1,54	1,25	1,6	1,52
1,26	1,33	1	2	2,14	1,26	1,33	2	2,24	1,6
1,44	1,34	1,15	1,39	1,35	1,15	1,4	1,25	2,24	1,4
1,04	1,25	1	1,79	1,27	1,17	1,28	1,6	1,63	1,33
1	1,25	1	1,8	1,26	1,09	1,28	1,67	1,67	1,32
1,13	1,11	1,19	1,79	1,43	1,09	1,15	1,23	1,63	1,29

work layers were calculated and the resulting layer was acquired.

The neural network's learning error was then calculated, which determined the difference between the true and estimated values of the variable. If the squared error was more than zero or 0,000001, the back-propagation process began (backward learning). It continued updating the connection weights backwards until reaching the input layer, and the forward process started again. This resulted in the trained models detailed in Figures 2 and 3.

Some negative estimators are present in the true

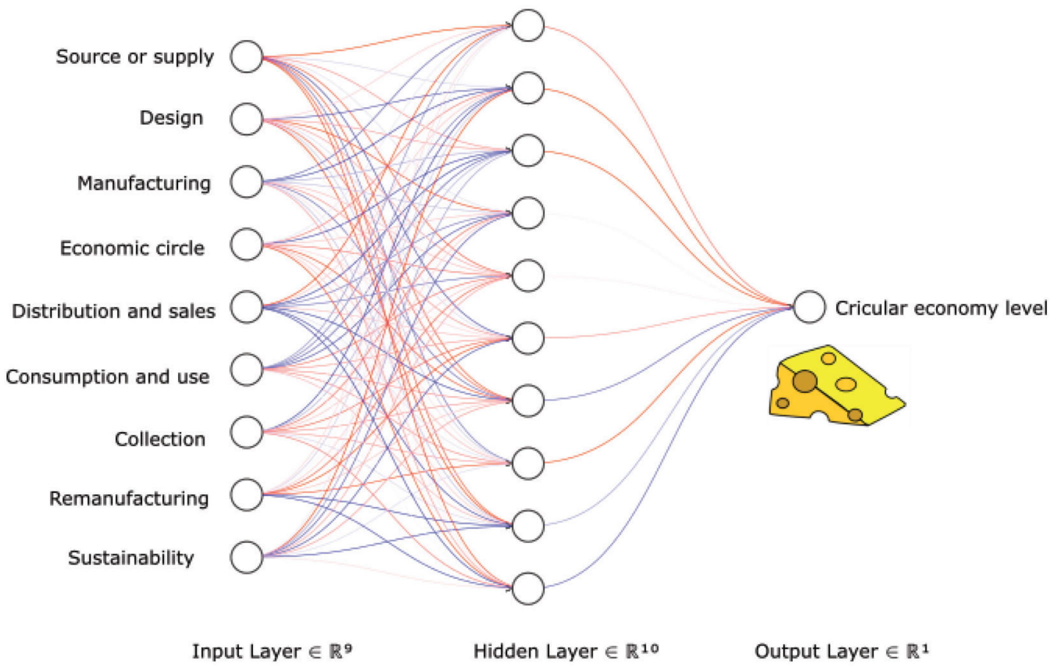

Figure 2. Heterogeneous weight multilayer perceptron neural network model

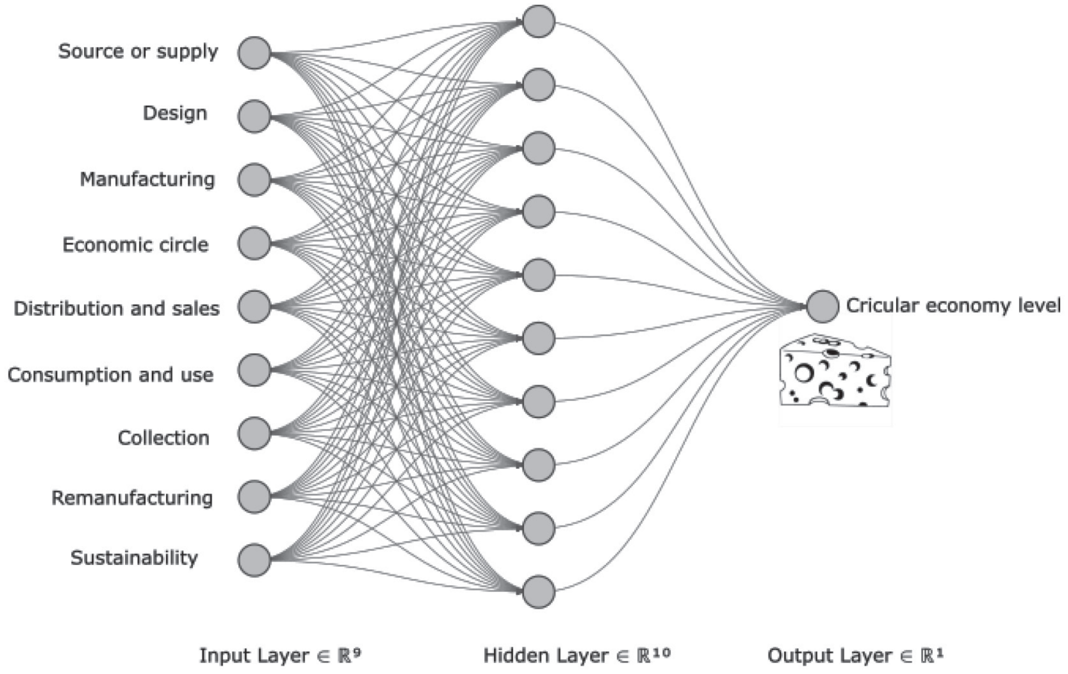

Figure 3. Multilayer perceptron neural network model of homogeneous weights

values and estimates, which correspond to 25% of the data used to test the model. These are preliminary findings, and the ranges must be refined. The learning procedure for neurons with heterogeneous weights took 972 steps to complete, while with homogeneous weights it was 612 steps. This shows that the performance of the number of iterations is lower in the network of homogeneous weights. The estimated results of the resulting variable with heterogeneous and homogeneous weights (Table 7) show that using

Table 7. Variable CEL results with heterogeneous and homogeneous weights

	Heterogeneous weights			**Homogeneous weights**		
	CEL	Estimated	Differences	CEL	Estimated	Differences
Stakeholders 1	2.08	2.11	0.03	2.08	2.111	0.031
Stakeholders 2	2.24	2.36	0.12	2.24	2.186	-0.054
Stakeholders 3	2.08	2.288	0.208	2.08	2.059	-0.021
Stakeholders 4	2.13	1.937	-0.193	2.13	2.122	-0.008
Stakeholders 5	1.41	1.416	0.006	1.41	1.428	0.018
Stakeholders 6	1.69	1.769	0.079	1.69	1.725	0.035
Stakeholders 7	1.46	1.491	0.031	1.46	1.481	0.021
Stakeholders 8	1.57	1.603	0.033	1.57	1.545	-0.025
Stakeholders 9	1.54	1.54	0	1.54	1.533	-0.007
Stakeholders 10	1.75	1.768	0.018	1.75	1.7	-0.05
Stakeholders 11	1.52	1.66	0.14	1.52	1.529	0.009
Stakeholders 12	1.6	1.723	0.123	1.6	1.633	0.033
Stakeholders 13	1.33	1.374	0.044	1.33	1.35	0.02
Stakeholders 14	1.32	1.37	0.05	1.32	1.329	0.009
Stakeholders 15	1.33	1.423	0.093	1.33	1.35	0.02
Stakeholders 16	1.38	1.582	0.202	1.38	1.358	-0.022
Stakeholders 17	1.35	1.485	0.135	1.35	1.34	-0.01
Stakeholders 18	1.32	1.563	0.243	1.32	1.325	0.005
Stakeholders 19	1.37	1.416	0.046	1.37	1.34	-0.03
Stakeholders 20	1.49	1.674	0.184	1.49	1.504	0.014

the neural network model results in superior estimates when the input variables have homogeneous weights in the initial layer.

To test the neural network model, 30% of the data that were not included in network training were used. The model was used, and the values were estimated using the procedure described above. These estimators were compared to the true values, and the Spearman correlation coefficient was determined to determine whether the data had similar values and was closest to 1 or -1. In terms of correlation, the chain with heterogeneous weights produced a high value of 0.9509787. However, the correlation factor of the variables with homogeneous weights was also high: 0.9957605. It is, therefore, possible to conclude that neural networks can be utilized to evaluate the circular economy level in agri-food chains using both homogeneous and non-homogeneous weights. The estimation using homogenous weights, on the other hand, is more precise. This facilitates decision-making with the circular economy's input variables. Depending on the variables and their weights, this analysis is convergent.

Based on the estimation results, the existence of Stakeholders where the CEL decreases is identified. This is evident in the Interested Parties are divided into two groups. A first group, which turns out to be the actors: 8; 9; 16; 17 and 19 and are located in the first stage of circular economy (Table 8). Therefore, the strategy to be used by this group is EPV. A second group, which is made up of the actors: 2;3;4; 10 and these are in the second stage of the circular economy level. In this sense, this group can select the EPV, A&P and IS strategies. This element offers a competitive advantage in the market.

3.2 Case study 2: Manabí shrimp agri-food chain, Ecuador

The investigated chain contains five links and 19 actors. Suppliers, producers, wholesalers or distributors, manufacturers, sellers, and customers are the many categories. The producers and merchants were grouped by cantons owing to the fact that there are a large number of them in the Manabí area. This product, although not the object of this investigation, is found in the Ecuadorian export catalog.

Following the identification of the actors, the checklist for assessing the level of the circular economy was applied to them. Tables 9 and 10 describe the values of the checklist application and the analysis of the nine dimensions with heterogeneous and homogeneous weights, respectively.

The network architecture, which is an input layer, was determined. It consisted of nine neurons for each covariate, seven neurons for the hidden layer, and one neuron for the output layer, as it was a prediction. As a result, the trained models were obtained, as detailed in Figures 4 and 5, above.

The learning procedure took 1372 steps to execute for neurons with heterogeneous weights, and 1413 steps for neurons with homogeneous weights. The estimated results of the output variable with heterogeneous and homogeneous weights (Table 11) show that using the neural network model produces superior estimates when the input variables have homogeneous weights in the initial layer. In terms of correlation, the outcome of the chain with heterogeneous weights was high, with a value of 0.9084951. However, the correlation factor of the variables with homogeneous weights was also high: 0.9468181.

It is, therefore, possible to conclude that both case studies obtained similar results. This demonstrates the systematization of neural networks for the study of the circular economy, and its potential for agri-food chains. These estimations allow early decisions to be made that promote the circular economy in the study chains, and therefore obtain improvements in less time.

Founded on the estimation results, the existence of Actors where the NEC decreases is identified. This is evidenced by the fact that the Interested Parties are divided into two groups. A first group, which is a single actor 2 and is located in the first stage of cir-

Table 8. Business model strategies recommendation from CEL evaluation

CEL: circular economy level		**Stakeholders**	Business model strategies for slowing loops			Business model strategies for closing loops		
Very low	≤ 1,5	8; 9; 16; 17; 19	EPV					
Low	(1,6; 2,5)	2;3;4; 10	EPV	A&P			IS	
Middle	(2,6; 3,5)		EPV	A&P	CLLM		IS	ERV
High	(3,6; 4,4)		EPV	A&P	CLLM	ES	IS	ERV
Very high	> 4,5		EPV	A&P	CLLM	ES	IS	ERV

Table 9. Input and response variables with heterogeneous weights

D1	D2	D3	D4	D5	D6	D7	D8	D9	CEL
3	4	4	4	4	4	3	4	4	3,7
1	1	1	5	1	1	1	1	3	1,7
1	2	1	4	1	1	2	1	3	1,8
1	2	2	2	3	2	2	2	3	2,1
3	3	3	3	3	3	3	3	3	3
3	3	3	3	3	3	3	3	3	3
3	3	3	3	4	3	3	3	3	3,1
2	2	1	3	1	1	1	1	1	1,4
3	3	3	3	3	3	3	3	3	3
3	3	3	3	3	3	3	3	3	3
2	3	3	4	3	3	3	3	3	3
3	3	3	3	3	3	3	3	3	3
3	1	3	4	2	2	1	2	3	2,3
1	1	3	2	1	1	2	2	2	1,7
1	4	4	4	4	3	3	4	3	3,3
3	3	3	4	4	3	4	4	4	3,5
1	1	1	5	1	1	1	1	4	1,8
2	2	3	5	3	3	1	3	3	2,8
1	3	3	3	4	2	2	5	4	3
2	2	3	3	3	2	2	3	3	2,5

Table 10. Input and response variables with homogeneous weights

D1	D2	D3	D4	D5	D6	D7	D8	D9	CEL
3	3	3	4	4	3	4	4	4	3,7
1	1	1	5	1	1	1	1	4	2,1
2	2	3	5	3	3	1	3	3	3,4
1	3	3	3	4	2	2	5	4	3,2
2	2	3	3	3	2	2	3	3	2,8
3	2	3	3	2	2	2	3	3	2,6
1	1	1	2	2	2	2	2	3	1,8
3	3	3	1	3	2	3	3	4	2,4
2	3	4	4	3	3	3	3	5	3,5
3	3	5	3	3	3	3	5	5	3,5
3	3	3	4	3	3	3	3	3	3,3
2	3	2	2	2	1	1	3	2	1,9
1	2	1	1	1	1	2	2	1	1,1
4	4	4	4	4	3	3	3	3	3,8
4	4	4	4	4	4	4	4	4	4
3	4	2	4	1	1	3	2	3	2,3
1	1	1	5	1	1	1	1	1	2
2	2	3	3	3	2	3	4	2	2,9
2	2	3	3	2	2	2	2	2	2,4
2	2	3	3	2	2	2	2	3	2,5

cular economy (Table 12). Therefore, the strategy to be used by this group is EPV. A second group, which is made up of the actors: 3;4; 6; 8 and 9 and these are located in the third stage of the circular economy level. In this sense, this group can select the strategies: EPV, A&P CLLM, IS and ERV.

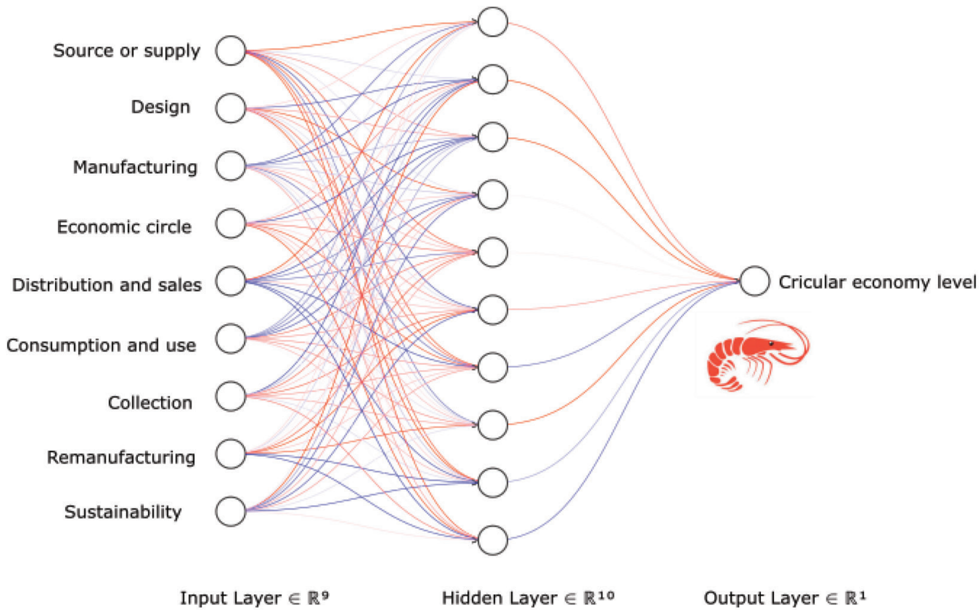

Figure 4. Heterogeneous weight multilayer perceptron neural network model

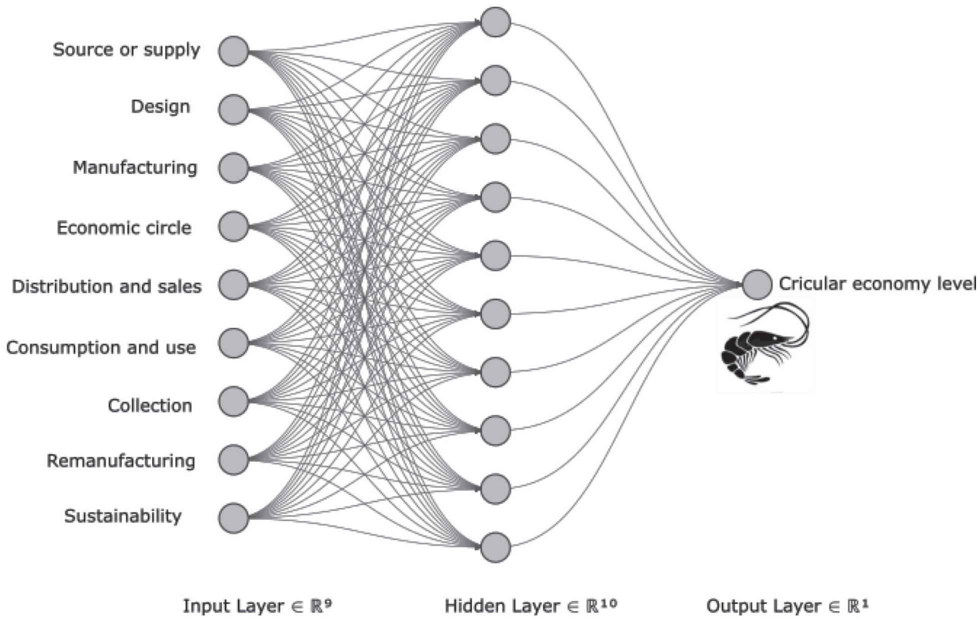

Figure 5. Multilayer perceptron neural network model of homogeneous weights

Table 11. Results of the generated variable NEC with heterogeneous and homogeneous weights

	Heterogeneous weights			**Homogeneous weights**		
	CEL_NH	Estimated	Differences	CEL_NH	Estimated	Differences
Stakeholders 1	1.57	0.398886	-1.1711139	1.65	1.67113	0.02113
Stakeholders 2	3	2.97	-0.03	1.76	1.437722	-0.322278
Stakeholders 3	2.68	1.64	-1.04	3.08	2.817554	-0.262446
Stakeholders 4	2.1	2.27	0.17	2.97	2.792681	-0.177319
Stakeholders 5	2.79	2.876799	0.0867992	2.97	2.991058	0.021058
Stakeholders 6	4	3.864137	-0.1358627	2.97	2.728183	-0.241817
Stakeholders 7	2.29	1.72847	-0.5615304	2.53	2.647472	0.117472
Stakeholders 8	2.04	1.084468	-0.9555324	3.08	2.921735	-0.158265
Stakeholders 9	2.89	2.59756	-0.29244	3.52	2.976028	-0.543972

Table 12. Business model strategies recommendation from CEL evaluation

CEL: circular economy level		**Stakeholders**	Business model strategies for slowing loops			Business model strategies for closing loops		
Very low	≤ 1,5	2	EPV					
Low	(1,6; 2,5)		EPV	A&P			IS	
Middle	(2,6; 3,5)	3; 4; 6; 8; 9	EPV	A&P	CLLM		IS	ERV
High	(3,6; 4,4)		EPV	A&P	CLLM	ES	IS	ERV
Very high	> 4,5		EPV	A&P	CLLM	ES	IS	ERV

4. Discussions

Studies of the circular economy in agri-food chains are carried out from different perspectives: the analysis of materials and their best use, the closed and open cycles of their flows, sustainability, circular business models, the use of waste, reuse, re-manufacture, and recycling. Despite this diversity, there remain gaps in the use of systemic tools that would enhance decision-making. The objective of the present study is, therefore, to fill one of these gaps.

Another important element in the analysis is the incorporation of stakeholders and the entire supply chain life cycle. This is the leveraging of multiple data sources that will enable an extended agri-food supply chain [48]. The elements included in this analysis encourage the increased use of contextual information and close the loop of sustainable agri-food chains through food waste reduction. The approaches require addressing the traditional stages of the supply chain. For example, in storage, it is vital to optimize warehouses and synchronize supply chain stages related to harvesting and distribution. In distribution, on the other hand, it is essential to analyze and control perishable products. Even though Lezoche et al. [49] found that very little is done to manage perishable agri-food products, integrated planning models must be used in agricultural supply chains. In this way, and as Cicullo et al. explain, ML techniques can offer new ways to look into how retailers, consumers, and the circular economy are connected [50].

In terms of the use of machine learning algorithms in agri-food chains, these results are consistent with those of Coulibally et al. [51] and can provide vital support to stakeholders (researchers and farmers) through the information and knowledge generated by the reasoning process of computational algorithms. In that study, they employed deep neural networks with transfer learning on millet crop images to build a system for the identification of mildew disease in pearl millet.

In the distribution and sales component, the use of ML can be of great importance. Several case studies have incorporated the application of ML in distribution and transportation systems [52], and how they can lead to the delivery time of a product to the right customers by generating better delivery routes and exploring consumer behavior [53]. This can impact decision making on delivery routes, predict food demand, supply raw materials and plan logistics [54]. The problem of delivery routes can be solved with ML by optimizing the location of the transport agent. Information about the current traffic situation Information about the current traffic situation is sent to inform them of the best route synchronously. Ensuring efficiency and on-time delivery facilitates consistent order delivery and even the resolution of problems such as running out of delivery agents or late deliveries. Similarly, the consumption and use factors are widely analyzed using ML techniques. For example, Ribeiro et al. [55] predicted consumer demand based on consumer buying behavior and perception using deep learning and ANN. In another study, Sharma et al. [56] found that a Bayesian network predicts consumer buying behavior of different food products and performs quality checks.

However, many limitations remain. There is still a medium level of information dissemination and knowledge sharing in agricultural developments [57], as well as empirical evidence is still needed on how computational tools and interventions are enabling farmers to make informed decisions. The integration of new technologies can enable the development of smart agriculture and address important agricultural goals such as saving water [58], [59], conserving soil [60], limiting carbon emissions, and increasing productivity by doing more with less [57]

Furthermore, there are regulations in Ecuador that favor the development of CE. These are based on: Carbon Quantification, the Carbon Footprint Reduction and Neutrality Program [61], the Organic Law of Circular and Inclusive Economy, and the book Bank of the Circular Economy in Ecuador. Despite this, there is evidence of weaknesses in agri-food chains, into which the actors should be integrated.

5. Conclusions

The use of a technique with which to forecast the circular economy in agri-food chains is currently essential when anticipating changes in customer needs, and it is also a necessary component for implementing the circular economy in these networks. This study discusses the use of neural networks to forecast of the circular economy level in the chains of cheese from Chone and shrimps from Manabí, Ecuador. It is also a necessary component for implementing the circular economy in these networks. This study discusses the use of neural networks to forecast the level of the circular economy.

The study concludes that, when employing neural networks for the forecasting problem of the circular economy in the chains studied, the use of homogeneous weights is recommended, since this enables decision-making under equal conditions. Furthermore, a set of approaches was applied to construct the neural network methodology. This demonstrated the algorithm's robustness and its applicability to a variety of problems. The results given were achieved after applying it to the Ecuadorian agri-food sector. This research validates the use of neural networks for different studies in supply chains and multiple variables.

The results of this study allow us to consider that future research goes deeper into the definition of circular economy strategies for agri-food chains based on their current conditions.

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