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The global innovation index in Colombia: An analysis and selection of influencing factors using artificial neural networks

El índice global de innovación en Colombia: un análisis y selección de los factores influyentes mediante el uso de redes neuronales artificiales

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Abstract

This research proposes a selection and classification model to understand what are the factors that impact innovation processes in the case of Colombia. The conceptual referents on the global innovation index and the technique of artificial neural network optimization are analyzed, the framework for the analysis and development through the networks is presented. Finally, the results obtained are shown, where it is found that 5 of the 133 most important variables to diagnose global innovation index are: intensity in local competition, foreign investment, credit, tertiary education, human capital and research, other variables discarded by the model for its minor importance are: GDP per unit of energy used or amount of total shares traded. The findings are expected to improve the decision-making process in prioritizing frameworks for regional and national innovation systems.

JEL Code: C53, C61, C63, O32
Keywords: innovation; indicators; artificial neural networks; modelling

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Resumen

Esta investigación propone un modelo de selección y clasificación para entender cuáles son los factores que impactan en los procesos de innovación para el caso de Colombia. Se analizan los referentes conceptuales sobre el índice global de innovación y la técnica de optimización de redes neuronales artificiales, se presenta el marco de trabajo para el análisis y desarrollo por medio de las redes. Finalmente, se muestran los resultados obtenidos, donde se encuentra que 5 de las 133 variables más importantes para diagnosticar el índice global de innovación son: intensidad en la competencia local, inversión extranjera, crédito, educación terciaria, capital humano e investigación, otras variables descartadas por el modelo como de menor importancia son: PIB por unidad de energía utilizada o cantidad de acciones totales tranzadas. Se espera que los hallazgos sirvan para mejorar el proceso de toma de decisiones en la priorización de marcos de trabajo para los sistemas de innovación regional y nacional.

Código JEL: C53, C61, C63, O32
Palabras clave: innovación; indicadores; redes neuronales artificiales; modelos

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Introduction

Concept of innovation

The concept can be found in the analysis of innovation in economics defined by Joseph Schumpeter (1934), who coined the concept of "creative destruction." According to Schumpeter, this process plays an important role in the historical evolution of capitalism (Muller, Heraud, & Zenker, 2017), where several types of innovation can be found: product, production and transportation, materials and sources, and market. Innovation is considered the main factor leading to economic and competitive growth and has been profoundly reflected upon in social, technological, and business circles (Jankowska, Matysek-Jedrych, & Mroczek-dabrowska, 2017). Innovation has had increasing importance as an indicator of prosperity in the world. This is due to improved creative capacity, which is not limited to advanced economies or high-tech sectors but is open as a global phenomenon (Dutta, 2017). This has led to the great industrial revolutions and, therefore, to more modern, high-tech, and advanced societies (Rao, 2010). The specialized literature has found two factors that favor a country's economic growth: first, human talent with a high level of knowledge training, and second, advances in information and communication technologies (ICTs). On the other hand, the maximum innovation potential of an economy is influenced by macroeconomic and microeconomic variables, such as the percentage of Gross Domestic Product, Percentage Expenditure on Innovation and Development, and Technology Gap, among others (Erciş & Ünalan, 2016). Nonetheless, this reductionist view of factors should be reformulated, mainly because it

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has been widely documented that innovation is neither deterministic nor linear in nature, but multi-agent, organic, and holistic (Diaz, 2019).

Innovation metrics and systems

One of the most representative worldwide indicators for measuring innovation among countries is the Global Innovation Index (GII). This index aims to establish assessment criteria for countries from higher to lower scores based on different innovation factors or variables. It is presented annually (Pençe, Kalkan, & Çeşmeli, 2019) and establishes the need to understand and manage innovation processes by country (Franco & Oliveira, 2017). What this index seeks is to capture the multi-variability in innovation and create an environment in which these factors can be continuously evaluated, as well as to establish metrics and approaches that capture the richness of innovation and go beyond the traditional approach, such as the number of scientific articles or patents, among others (Cornell University, INSEAD, & WIPO, 2020). Year by year, the GII considers new factors to be evaluated, some of which are constant over time, and others are variable. Table 1 presents the number of factors evaluated for 2013-2019 and their respective GII scores for Colombia.

Table 1
Number of aspects evaluated and rating per year in the GII (Global Innovation Index, 2020)

Year	Number of aspects evaluated in the GII	Global Innovation Index Rating
2013	122	60
2014	109	68
2015	107	67
2016	110	63
2017	109	65
2018	108	63
2019	108	67

Source: created by the author

Innovation systems and their concepts were addressed by Freeman (1987), Lundvall (1982), and Nelson (1983) (Rinkinen, Oikarinen, & Melkas, 2016). The concept has gained great popularity largely due to increased international competition in a rapidly globalizing economy. It has stimulated innovation capabilities and competitiveness among regions (Doloreux & Parto, 2005) and can be defined from various approaches: national, regional, sectoral, or technological. Although there is no universally accepted definition for this concept, there is a certain degree of convergence among theories that include localized networks of actors and the generation, transfer, modification, creation, diffusion, and use of knowledge and innovation (Valdéz & León, 2015; Carlsson et al., 2002) within a production structure of a region.

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Innovation systems are based on many research fields, including evolutionary economics, institutional economics, cluster theory, new regional economics, learning economics in systems and innovation economics, and network theory (Stuck, Broekel, & Revilla, 2016). Additionally, innovation systems are understood as an arrangement of components in constant relationship and change, and can be considered a complex system, as they are composed of other subsystems of different natures and are strongly connected (Muller, Heraud, & Zenker, 2017).

The study of innovation systems consists of emphasizing the competitive advantages of each nation or region to generate innovation, which depends on the relationship of some key components arranged in subsystems of exploration and exploitation, which are made up of: companies, university institutions, mediators, and innovation policies (Doloreux, 2002). Each of these actors belonging to the system can be described as (Zollo, De Crescenzo, & Ponsiglione, 2011):

- Exploiters or companies: they transform knowledge into value in the market.
- Explorers or university institutions: producers of knowledge, they explore the frontiers of knowledge producing new ideas, new methods, and new techniques available to companies.
- Catalysts or mediators: facilitators in the complex process of knowledge transfer, adaptation, and utilization as technological incubators or innovation mediators.
- Government or innovation policies: in charge of guiding, organizing, and coordinating networks of actors, providing scientific and technological competencies. They are responsible for providing whatever is necessary to generate innovation.

The GII evaluates the strengths and weaknesses of national innovation systems using two sub-indices, inputs and outputs, from which the efficiency ratio is derived, which expresses how efficient a country is in terms of innovation. The input sub-index comprises institutions, human capital and research, infrastructure, market sophistication, and business sophistication, while the output sub-index comprises knowledge, technology, and creativity (Departamento Nacional de Planeación, 2018).

According to the scores obtained in the GII, Colombia as a country has been classified in a medium innovation cluster (Jankowska, Matysek-Jedrych, & Mroczek-dabrowska, 2017). This means that there are still weaknesses in the interdependence of the actors of the innovation system, which means that coordinated strategies and measures to support innovation processes are lacking. From this perspective, Colombia has also been characterized by a late industrialization process still under construction.

Based on this, there is a need to analyze the GII variables to find which are most important and relevant to the impact of the GII. In general, the amount of data obtained and the number of aspects to be evaluated constitute an important information base that should be analyzed through methodologies coming from artificial intelligence and deep learning that will help to analyze the data and establish models, which through other methodologies would be complex (Pençe, Kalkan, & Çeşmeli, 2019).

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Artificial intelligence

The current methodologies from artificial intelligence used in the analysis of information—added to the importance of data in the growing economy of the fourth industrial revolution—have been summarized in the following statement: "Big Data is the new oil," according to IBM's CEO. Recent studies have demonstrated the impact and power of data in modern life (Iqbal et al., 2018). Many tools based on data mining have been generated from this, which have been used to analyze all types of databases. These tools have been called supervised and unsupervised techniques, which have been used to perform two types of analysis: predictive and descriptive. One of the focuses of descriptive analysis is the selection or extraction of factors of interest within a dataset. This is a general problem in machine learning, which can identify a group of variables that have more influence (Visalakshi & Radha, 2015) on some dependent event. Likewise, it is useful for reducing noise or redundant variables, which could degrade the system's performance (Devi & Sabrigiriraj, 2018). In this case, these are the factors that have the greatest influence on the GII for Colombia.

There are several techniques to perform a descriptive analysis for the selection of factors, including probabilistic methods, evolutionary methods, and artificial neural networks (ANNs). These were studied by McCulloch and Pitts in 1943 to propose computational models with learning abilities through neural feedback (Baum, 1988). Nowadays, it is essential to associate this type of network with learning, which is essential for training machine intelligence; however, the learning process in the context of ANNs can be seen as a problem of updating and loading data. The preference for ANNs over other types of techniques is because they constitute one of the most powerful and efficient tools for classification and pattern recognition, planning, prediction (Hanafizadeh, Ravasan, & Khaki, 2010), control, and optimization due to their nonlinear and nonparametric adaptive learning properties (Blanco et al., 2013). Moreover, they constitute a computational paradigm that provides various nonlinear mathematical models used to study a wide range of statistical problems (Blanco et al., 2013). Finally, ANNs are not far from the more traditional statistical and probabilistic methods. In fact, they can be considered a regression technique, represented by a high nonlinearity between the dependent and independent variables (Geem & Roper, 2009).

The rationale for the preferred use of ANNs as an analysis technique lies in its principles based on the neurophysiological concept of the human brain (Xiang & Deng, 2010), and its cells—neurons—which have several characteristics desired by any computational system. This has increased the research and application field for the functioning of ANNs. Such networks learn from their environment by making use of the available information. Therefore, they are not programmed, but trained. As a result, they can deliver good results in the short term (Kigami, 2001). The main attributes found in this type of technique are the following: learning from experience, generalization from examples, development of faster solutions, computational efficiency, and nonlinearity.

ANNs contain several algorithms: perceptron, backward and forward propagation, madaline, and radial basis networks, among others. The multilayer perceptron is the most commonly used ANN (Blanco et al., 2013, Hamadache et al., 2017) in various disciplines for aspects such as classification and prediction of variables. The multilayer perceptron belongs to the set of supervised techniques, which means that it is necessary to provide the model with multiple input variables and one or more desired outputs (Serrano-Cinca, 1996).

Given the above, this research proposes the application of an ANN as a novel methodology that will allow innovation policy decision-makers to select the critical factors that influence the GII for Colombia as a strategy to compete and compare with other countries.

Method

Review of the literature

For the development of this research, the data set was collected from the open data page Global Innovation Index (2020), and the literature review has three main elements: innovation, global innovation index, and artificial neural networks. The search for these elements was performed in the indexed databases SCOPUS, Science Direct, and JSTOR, and the ResearchGate platform as an additional repository of information. The search was done through the following search equations: (TITLE-ABS-KEY ("feature selection") AND TITLE-ABS-KEY ("machine learning")), (TITLE-ABS-KEY ("feature selection") AND TITLE-ABS-KEY ("neural networks")), (TITLE-ABS-KEY ("feature selection") AND TITLE-ABS-KEY ("neural networks")) AND (LIMIT-TO (ACCESSTYPE(OA))) AND (LIMIT-TO (PUBYEAR , 2020) OR LIMIT-TO (PUBYEAR , 2019)) and (TITLE-ABS-KEY ("feature selection") AND TITLE-ABS-KEY ("machine learning") AND TITLE-ABS-KEY ("Artificial Neural Networks")) AND DOCTYPE (ar) AND ACCESSTYPE (OA) AND PUBYEAR > 2009, with their respective recovered documents: 11100, 7264, 538, and 166. Finally, the literature review retrieved 40 documents relevant to the research. 97.5% are in English; 53% were published within 2015-2020.

In works related to the subject of this article, authors such as Dalmau et al. (2010) have used the variable extraction method implementing ANNs in complex and non-balanced anaerobic digestion processes. Additionally, Khumprom, Grewell, and Yodo (2020) have used deep learning and ANN as a method of variable selection in gas turbine models to reduce the number of variables in the model complexity. It has been found that using such methods has greater advantages over traditional methods, such as physical or traditional statistical methods, since their performance is superior in the case of complex models with high nonlinearity (Khumprom, Grewell & Yodo, 2020). In natural language processing, especially in emotion recognition, ANNs are fundamental since language and emotions are computationally complex topics to address. This is how Farooq et al. (2020) use ANNs to classify and extract variables to understand emotions as a speech signal. In this case, different classifiers such as support vector machines, random forests, nearest neighbors, multilayer perceptron, and even naive Bayes are found to solve the problem of dimensionality of a dataset (Devi & Sabrigiriraj, 2018; Visalakshi & Radha, 2015).

Another application in the literature review is the use of ANNs in the economic and financial sectors. Liu and Schumann (2005) use this method to select variables in credit processes, which, as stated, are in some cases arbitrarily dominated. Huotari, Savolainen, and Collan (2020) used deep learning using convolutional networks in stock selection for the S&P 500, in this case to optimize investment portfolios. Finally, ANNs have been used prolifically and constantly in health processes, especially to classify and select. In this case, Mourad et al. (2020) use factor selection to identify the most important variables to study the cause of death of thyroid cancer. In this study, 7 variables are considered, and the three most important ones are found after applying the selection algorithm. As can be seen, there is great interest in applying these optimization methods—artificial intelligence and deep learning—in many areas of knowledge, such as medicine, finance, economics, bioinformatics, marketing, or innovation and its related systems.

Methodology

The working methodology used for this research consisted of taking the GII as a reference since the main objective of this index is to measure innovation robustly, including many variables. This method will show the most and the least important variables to promote strategies in innovation policies through the AI ANN multilayer perceptron method with a backpropagation algorithm. It is necessary to clarify that it is not considered a statistical technique. Therefore, the method's potential is that the network is trained with the data of the independent input variables available; these are the aspects of the GII. This means that the method is only as accurate as the data used to train the system and the knowledge and mastery of the problem.

In this part of the section, the proposed methodological algorithm is described using an ANN to select factors, which is presented in Figure 1. In this, the target variable or output layer, which is the GII, is selected. Then, the required datasets from 2013 to 2019 are obtained from the Global Innovation Index website, and the data are preprocessed to be loaded into the model. Inconsistency or incompleteness problems are common; therefore, missing data are obtained in some cases using the average value (Bansal et al., 2018). Subsequently, the neural network architecture is constructed, and its input layer and its hidden layers are detailed. Finally, the ANN where the model predictions are validated is trained, and the factors that positively impact the network's performance are selected.

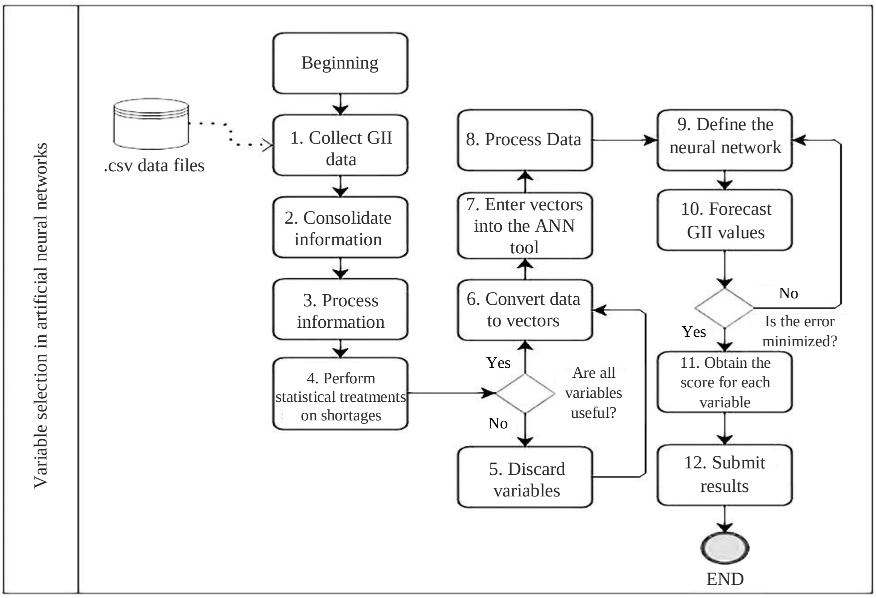

Figure 1. Research Methodology
Source: created by the author

The following is the technical data sheet for the research described in Table 2.

Table 2
Technical research datasheet

Universe	Global Innovation Index Indicators
Geographic scope	National (Colombia)
Data source	Global Innovation Index (Global Innovation Index, 2020)
Total number of indicators to be evaluated	134 indicators for Colombia
Sample design	134 indicators with 7 years of data for each indicator
Analysis dataset structure	938 total data items
Data collection period	2013-2019
Type of sampling	Complete Non-probabilistic
Analysis techniques	Descriptive Analysis and Artificial Neural Networks
Software used	NETLOGO version 6.0.4 and IBM SPSS version 19

Source: created by the author

Construction of the neural network for factor selection

ANNs are techniques for qualitative and quantitative data analytics inspired by how the brain processes information (Hajek & Henriques, 2017). Their basic element and unit is the neuron or node, the simplest processing unit. These are organized by three types of layers: input, hidden, and output (Geem & Roper, 2009). Each node is linked to n-input units through n-directed connections and is characterized by a boundary value, a univariate activation function, and a vector of weights (Leshno & Spector, 1996). Neural network models accept many inputs, summing them in a weighted manner. Usually, nonlinear functions are applied to generate results (Kuzey, Uyar, & Delen, 2014) and transmit them to another neuron. These results are set as future inputs to the network. The advantages of using neural networks lie in the need to work with decision processes when large amounts of data and hidden patterns are found, scenarios where the development of traditional mathematical and statistical models is difficult and complex (Hanafizadeh, Ravasan, & Khaki, 2010). Thus, one of the main advantages of ANNs is their generalization capabilities, which are not based on preliminary or pre-established models. These models have become robust and reliable even if there are outliers or missing data (Di Tollo et al., 2012).

Like biological neurons, one of the main attractions of neural networks is their ability to learn and adjust to the conditions of the input and output layers. Each layer has a number of associated neurons, and the number of hidden layers or nodes determines the complexity of the final model (Blanco et al., 2013). Therefore, the more layers a neural network has, the deeper it will be and the better the features it will create to select and classify.

Within ANN models, the multilayer perceptron with the error backpropagation algorithm is the most popular model for prediction and factor selection. Figure 2 shows the general structure of this type of neural network.

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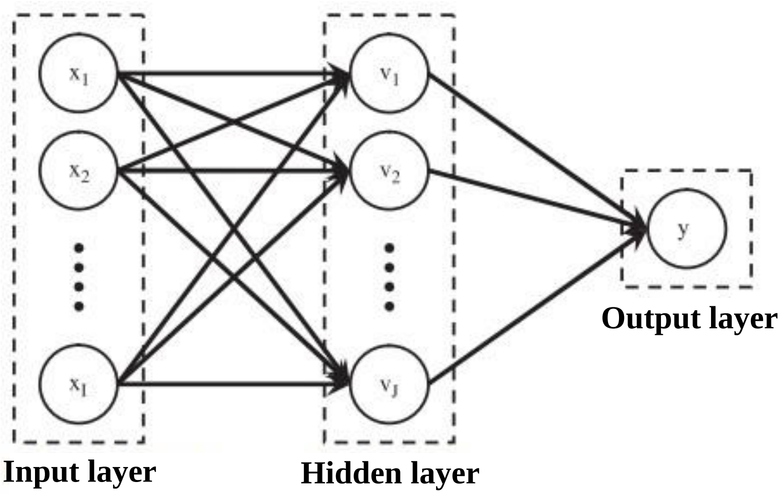

Figure 2. Artificial neural network concept
Source: Adapted from (Geem & Roper, 2009)

First, there is an input layer with a given number of units, cells, or nodes; then, multiple layers with intermediate units; and finally, an output layer. Each unit or node is connected to a previous and next stage unit, and a synaptic weight associated with the output node (Baum, 1988). The neural network output found in the final layer is associated with Equation 1. It should be considered that each neuron of the hidden layer and the input layer contribute weighted weights and values that are adjusted in the network's learning process (West, 2000). Likewise, the ANN uses several activation functions, such as the hyperbolic tangent and the sigmoid function (Kigami, 2001), presented in Equation 2.

$$Y_k = f_h \sum_{i=1}^{n} w_{ij}\, x_i + w_{jb} \tag{1}$$

Where:

Y_k: are the neurons of the output layer.

f_h: Is the network activation function.

w_{ij}: are the synaptic weights of the learning and adaptation process.

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$$Y_j = \frac{1}{1 + e^{-\sum w_{ij} X_i}} \tag{2}$$

Where:

α: Is the slope parameter of the curve.

v: Is the weighted sum of the neuron

ANN acts through learning algorithms, which adjust their architecture and parameters to minimize an error function that indicates the degree of data fit (Kengpol & Wangananon, 2006) or the learning rate of the network measured through the variance (Xiang & Deng, 2010) to measure the performance of the model (Hamadache et al., 2017). Therefore, one of the objectives of ANN is to minimize the error function (called Loss Function) between the desired output and the output of the neural model from a set of already classified observations (Kengpol & Wangananon, 2006). The error function is defined as the root mean square error (RMSE), and the result of the process is estimated through this function. The value can be calculated as shown in Equation 3.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} (y - y_i)^2}{n}} \tag{3}$$

The ANN innovation model can be developed using several innovation indicators, which are the independent variables to predict the innovation indicator (Nair, Kumar, & Ahmed, 2014). Therefore, for the construction of the multilayer perceptron type of ANN with a backpropagation algorithm, 133 independent variables or factors found in the Global Innovation Index will be selected, structured in 7 major groups to reduce the visual complexity of the proposed network: Institutions, Human capital and research, Infrastructure, Market sophistication, Business sophistication, Knowledge and technology, and Creativity. Table 3 shows the parameters and starting information for the constructed network.

Table 3
Neural network construction

	Neural network information	
Input layer	Independent variables factors	133
Hidden layers	Number of hidden layers	2
	Number of hidden layer units	100
	Network activation function	Hyperbolic tangent
Output layer	Dependent variables	1
	Number of units	1
	Activation function	Hyperbolic tangent
	Error function	Sum of squared errors
Sample	Training	80%
	Test	20%

Source: created by the author

Figure 3 shows the construction of the multilayer perceptron ANN, with its three layers of neurons. The input layer contains the 133 independent variables. Nevertheless, due to the complexity and size of the network presented, the hidden layer, which, using the activation function, adjusts the weights in the neurons, was used for its groupings. The first layer of the network neurons spreads through the upper layers until an output is generated, which is compared with the result obtained from the output neurons with the desired result, i.e., with the results of the Global Innovation Index. Through the RMSE function, this is transmitted backward so that each neuron receives the approximate participation error.

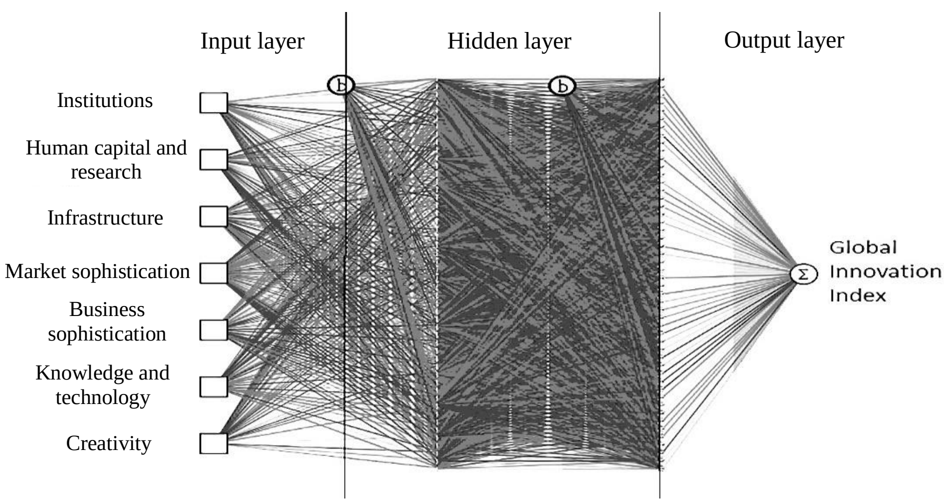

Figure 3. Multilayer ANN Perceptron
Source: created by the author

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Results

The network conformation structure comprises 133 variables, with 2 hidden layers. The number of hidden nodes was 100 in each layer, and 1 node was considered in the output layer, representing the GII. The dataset was divided into 2 groups: 1 of them composed of 80% for training data and 20% for test data on the network. The hyperbolic tangent function was used as the transfer function of the hidden and output layers.

As can be seen in Table 4, results were obtained for the ANN model, where the performance of the network in its training and testing phase shows a small root mean square error (RMSE) of 0.061 and 0.000, respectively, indicating that the data obtained by the network in its prediction were significantly close to the real data provided for the network. In addition, other architectures were compared, where the quadratic errors in training for the other ANNs were: 0.372, 0.087, and 0.098, respectively. In the test stage, the squared errors were 0.005, 0.104, and 0.558. It is thus found that the results of the selected network are better.

On the other hand, Figure 4 shows the relationship between the predicted value and the real value of the GII, in which it can be seen that a very good result was obtained, which was notably high in the coefficient of determination and therefore of correlation, which once again guarantees excellent forecasts on this index and the correct selection of variables. By comparing the results with similar networks, it can be found that the coefficients of determination are lower, indicating a poor fit to the data; the results were 0.879, 0.897, and 0.558, showing that the selected ANN has a better fit to the predicted data.

Table 4
ANN Model Results

Summary of the model		
Training	Sum of squared errors	0.061
	Relative error	0.038
	Stopping rule used	1 consecutive step without error reduction
	Training time	00:00:00.106
Test	Sum of squared errors	0.000
	Relative error	It cannot be calculated. The dependent variable may be constant in the test sample.

Source: created by the author

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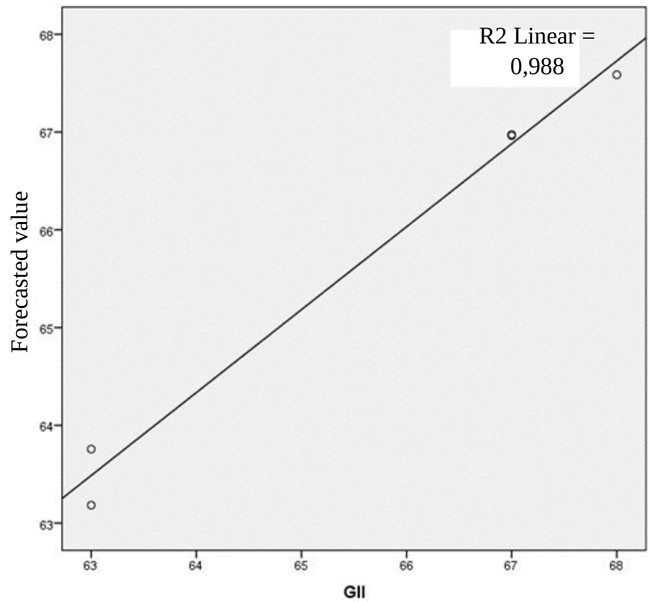

Figure 4. Model fitting and prediction

To select the factors with the most importance and influence on the GII, the importance of the independent variables was used through their weighted percentage of importance and their normalized percentage of importance. Both measures indicate how much the value of the dependent variable changes for the ANN model for different values of the independent variable. The importance indicator consists of weighting each variable analyzed as a percentage and ordering them from highest to lowest. The normalized importance results from the values divided by the highest importance values expressed as a percentage. Thus, the ANN model created responds to the classification of factors and the importance of the variables for the influence of the output in the model. Table 5 shows the fifteen most important variables obtained in the exercise, which account for approximately 40% of the contribution to the Global Innovation Index. It appears that the variables intensity of local competition, investment, credit, tertiary education, human capital and research, knowledge workers, and knowledge absorption, among others, have the greatest effect on how the ANN ranks the GII.

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Table 5
Importance of independent variables in the ANN model

Importance of the independent variables			
Variable code	Explanation	Importance	Standardized significance
V54	Intensity of local competition	3.94%	100%
V86	Foreign direct investment net outflows	3.56%	90.4%
V46	Investment	3.11%	78.8%
V42	Credit	3.07%	77.8%
V43	Ease of obtaining credit	3.04%	77%
V20	Tertiary education	2.93%	74.4%
V14	Human capital and research	2.69%	68.1%
V37	Ecological sustainability	2.62%	66.4%
V56	Knowledge workers	2.60%	66%
V35	Logistics performance	2.36%	59.9%
V68	Knowledge absorption	2.33%	59%
V32	Online e-participation	1.97%	50%
V51	Trade and competition	1.86%	47.1%
V66	Joint venture/strategic alliance deals	1.81%	45.9%
V48	Market capitalization	1.62%	41%

Source: created by the author

Finally, Figure 5 shows the normalized significance for the entire set of 133 independent variables used in the ANN model. The normalized importance chart is a bar chart of Table 5, ranked in descending value of importance. Variables that contribute little to the GII can be seen. In this case, gross domestic product per unit of energy contributes 0.01%, and the total number of shares traded contributes 0.02%.

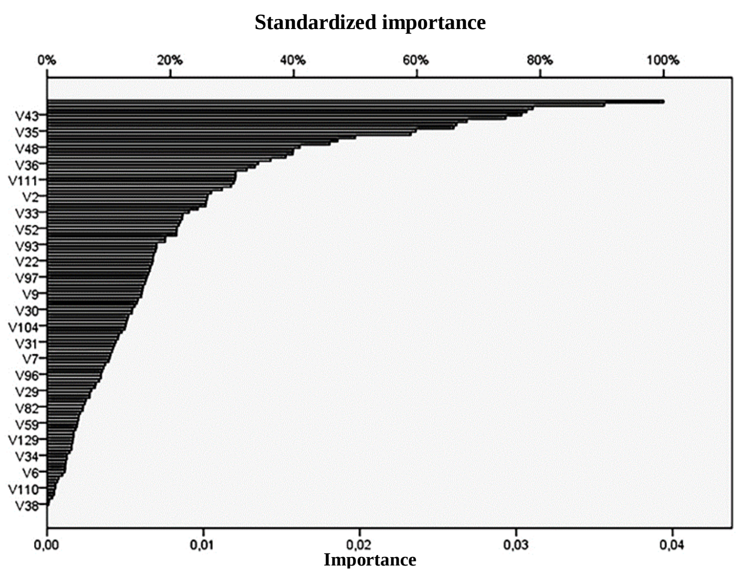

Figure 5. Importance of GII factors
Source: created by the author

Conclusions

In this article, an ANN model with a backpropagation algorithm was developed, demonstrating that this type of computational method is capable of performing tasks of high complexity and with a large number of variables with statistical accuracy.

The proposed ANN model is relevant to select the factors that determine and most influence the Global Innovation Index in Colombia. The study showed that the groups with the most important factors for the indicator are those related to human capital and research, infrastructure, market sophistication, business sophistication, and only one factor in knowledge and technology.

Regarding the tool used, it is important to clarify that within the method of application of neural networks there is a disadvantage: there is no single known procedure that guarantees that the global solutions found manage to find a configuration of synaptic weights that minimizes the error criterion. Therefore, one of the multiple possible local minima is obtained through one of the many rules proposed in the literature. On the other hand, as has been explained, artificial neural networks are a simplification of the biological process, and the model created does not capture the dynamics and spatiotemporal properties, which are important in the biological process. Nevertheless, as already mentioned, artificial neural networks can accurately approximate various types of complex relationships but with clear limitations.

It should be noted that the configuration of ANNs depends on the different learning algorithms, e.g., good generality and minimal errors can be achieved with small networks, although increasing the number of layers and nodes can yield similar results with smaller error rates. In general, it is advisable to have long initial layers with many nodes and small hidden layers, although everything will depend on the context. In this case, there was a large layer of 133-factor nodes and two smaller hidden layers, which allowed for greater error distribution and better learning.

As future research work on this topic, it could be proposed to compare the performance of ANNs with other types of metaheuristic approaches, such as genetic algorithms and fuzzy logic, among others, or with traditional methods in science, such as statistics and linear regression models, especially to examine the effectiveness of the methods.

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