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A New Hybrid Approach for Clustering, Classification, and Prediction of World Development Indicators Combining General Type-2 Fuzzy Systems and Neural Networks

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Abstract: Economic risk is a probability that measures the possible alterations, as well as the uncertainty, generated by multiple internal or external factors. Sometimes it could cause the impossibility of guaranteeing the level of compliance with organizational goals and objectives, which is why for their administration they are frequently divided into multiple categories according to their consequences and impact. Global indicators are dynamic and sometimes the correlation is uncertain because they depend largely on a combination of economic, social, and environmental factors. Thus, our proposal consists of a model for prediction and classification of multivariate risk factors such as birth rate and population growth, among others, using multiple neural networks and General Type-2 fuzzy systems. The contribution is the proposal to integrate multiple variables of several time series using both supervised and unsupervised neural networks, and a generalized Type-2 fuzzy integration. Results show the advantages of utilizing the method for the fuzzy integration of multiple time series attributes, with which the user can then prevent future threats from the global environment that impact the scheduled compliance process.

Keywords: clustering; generalized Type-2 fuzzy system; neural networks; prediction

MSC: 03B52

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1. Introduction

For reasons of security and logical access to data, in organizations, users have access to the essential information to carry out work. Also, we face the challenge of integrating general information from different sources, of which the historical detail is protected by the owners of the corresponding information.

As regards the analysis of time series composed of indicators or criteria, we could point out that most of these data represent the integration of multiple variables and classifications made by experts in the field when it comes to analyzing multiple time series [1–3].

Related to the above, risk management contemplates economic, environmental, and human factors, among others, the latter being the one that has constantly attracted the attention of organizations in recent decades, given that a person has logical or physical access to an information system and may enter, alter, or share sensitive information with third parties, which may result in losses of various types [4–6].

Likewise, another approach contemplated by risk management around the human factor is decision making, since if the person responsible for deciding lacks complete, relevant, and timely information or is unfocused due to internal or external factors, it could cause an inappropriate decision to be made, which is reflected in losses of various types.

As part of the strategies for risk management, programs for risk prevention and response are carried out in organizations, investments are made in computer security tools and equipment, and institutional guidelines and policies are disseminated in the organization [7–9].

For example, as part of these continuous improvement programs, new models are constantly sought that adjust to these needs that arise from the growing uncertainty and changes in the environment, which provide a way to balance and share responsibility in decision making through the integration of indicators from different sources and adaptability in the midst of uncertainty.

Contemplating this aspect of risk management with a focus on the human factor, we present a model for clustering, classification, and prediction of indicators using intelligent computing methods that have proven to be effective in solving complex problems [10–12], primarily supervised [13,14] and unsupervised [15,16] neural networks (NNs) and Type-1 and Type-2 fuzzy inference systems [17,18].

One of the advantages of this method is that it is possible to combine artificial neural network models and use sets of fuzzy systems to perform classification, clustering, and time series prediction by working or forming segments of information grouped by similar attributes.

This approach differs from most existing intelligent computational methods [12,19] in that to carry out the clustering, classification, and time series prediction, it focuses on combining supervised and unsupervised algorithms to carry out the training of the neural networks.

In addition to the previous point, the model contemplates uncertainty management for decision making and the integration of results utilizing fuzzy systems to carry out the classification and integration of the obtained results. It allows us to obtain results for one or multiple variables.

Thus, the contribution of the model contemplates the combination of different types of NNs to perform clustering and prediction of multiple time series and subsequently use different levels of Type-1, Interval Type-2, and General Type-2 fuzzy systems as integrators of multiple results to finally obtain a general classification.

This paper is structured as follows. In Section 2, basic concepts are presented. The problem at hand is outlined in Section 3. The methodology used is outlined in Section 4. The experiments and results are contained in Sections 5 and 6, respectively. Lastly, in Section 7, the conclusions are offered.

2. Basic Concepts

In this section, a theoretical summary of the methods used to design the proposed model, focusing on the general concepts of neural networks and fuzzy systems to address intelligent computing techniques as bioinspired methods is presented.

2.1. Neural Networks

The prediction of time series behavior using artificial neural networks (ANNs) has been extensively investigated because they learn based on non-linear relationships between the inputs available and the desired outputs and their great capacity for pattern recognition.

Although ANNs are a powerful tool for processing an infinity of data, their success has been demonstrated in applications from different areas of knowledge [20,21]. Today, we can find different applications that consider ANNs to solve different problems in which they have been proven to be effective and precise [22].

For the case where the algorithm uses input and output data as a way to carry out training, we can point out that it is a supervised neural network model [23–25], unlike unsupervised neural network models [26], where only input data are used to form clusters that represent characteristics of the data through classes [27].

2.2. Type-2 Fuzzy Systems

A fuzzy system is composed of a knowledge base represented by fuzzy rules, a database that stores the parameters and specifications of the membership functions, and a mechanism that simulates reasoning.

In general terms about the theory of fuzzy logic, we can point out that its basic definitions apply to Type-1 and Type-2 fuzzy sets. A Type-2 fuzzy system is integrated with fuzzy if–then rules and membership functions where the antecedent or consequent has Type-2 fuzzy sets that are composed of Type-1 fuzzy sets [27].

It is a generalization of Type-1 fuzzy logic since, in addition to considering the uncertainty in the linguistic variables, this uncertainty is also considered in the definition of the membership functions [28].

A General Type-2 fuzzy set A is formed by a primary variable x with domain X and a secondary variable u with domain J_x, and it can be formulated in (1):

$$A = \{((x,u), u_A(x,u)) \mid x \in X, u \in J_x, \ J_{x,} \subseteq [0,1]\} \tag{1}$$

The Footprint of Uncertainty (FOU) is mathematically expressed in (2):

$$\text{FOU}(A) = \left\{(x,u) \middle| \, x \in X \text{ and } u \in \left[\underline{\mu}_A(x), \overline{\mu}_A(x)\right]\right\} \tag{2}$$

where $\underline{\mu}_A(x)$ and $\overline{\mu}_A(x)$ are the lower and upper membership functions, respectively.

Now, in an Interval Type-2 Mamdani Fuzzy Inference System, a process like that of a Type-1 is carried out; the main difference is the activation forces of the upper and lower rules, as mathematically expressed in (3):

$$R^l \ : \text{IF } x_1 \text{ is } F_1^l \text{ and} \ldots \text{and } x_p \text{ is } F_p^l \text{ THEN } y \ is\ G^l \tag{3}$$

where $l = 1, \ldots, M$.

3. Problem Description

The World Development Indicators (WDI) are the World Bank's compilation of cross-country indicators. It is a historical statistical set of significance and is focused on global development and monitoring the level of poverty. During its compilation, different internationally recognized sources are used. Therefore, they represent the most up-to-date and accurate global development data available.

The persistence and constant analysis of indicators and criteria worldwide seek to make improvements in institutional aspects, which, due to their origin, tend to change or modify slowly but their impact has broad coverage.

So, our approach is to achieve an integration of results derived from the use of neural networks and be able to compare each indicator evaluation process for the corresponding fuzzy classification. In addition, the management of uncertainty in decision making is based on the integration carried out and the combination of WDI variables [29,30].

Moreover, based on the behavior of multiple economic and non-economic variables during a given period, we will be able to identify key aspects in which improvement is viable.

Thus, to get the overview, the next thing is to combine the results of the neural networks by using several Type-1 and Type-2 Fuzzy Inference Systems (FIS) as integrators [18]. After, we make comparisons, with which it will be possible to analyze economic progress, stagnation, and setbacks on a given date.

In this case study, we are referring to a sample of 208 countries, which present similarities and contrasts. Also, we selected twelve datasets for each country. In Table 1, the list of the variables (time series) that were considered for clustering and prediction criteria in this work can be found, where the code, name, and period are shown for each variable. It should be noted that no preprocessing was carried out, and this is because it was a World

Bank compilation of relevant, high-quality, and internationally comparable statistics about global development, which means that the data are ready to be used in this research.

Table 1. List of time series dataset.

No.	Variable Code	Variable Name	Period
1	TSS1	Access to electricity	2000–2021
2	TSS2	Birth rate	1990–2021
3	TSS3	Death rate	1990–2021
4	TSS4	Life expectancy at birth (female)	2000–2021
5	TSS5	Life expectancy at birth	1990–2021
6	TSS6	Life expectancy birth (male)	1960–2021
7	TSS7	Population growth	1960–2022
8	TSS8	Population	1960–2022
9	TSS9	Population (female)	1960–2022
10	TSS10	%Population (female)	1960–2022
11	TSS11	Population (male)	1960–2022
12	TSS12	%Population (male)	1960–2022

For this case study, we use the classification of seven regions of the World Bank for the selected sample of countries (Table 2), where the code, name, and total countries are shown for each region.

Table 2. Total countries by region.

No.	Region Code	Region Name	Total Countries
1	R1	East Asia and Pacific	35
2	R2	Europe and Central Asia	53
3	R3	Latin America and Caribbean	41
4	R4	Middle East and North Africa	20
5	R5	North America	3
6	R6	South Asia	8
7	R7	Sub-Saharan Africa	48

4. Method

We propose a model for clustering, classification, and time series prediction that consists of two phases (Figure 1). In the first one, we use a non-linear autoregressive (NAR) neural network for prediction, a self-organizing map (SOM), and competitive neural networks for clustering into six classes.

Subsequently, in the second phase, we use different levels of Type-1, Interval Type-2, and General Type-2 fuzzy systems as integrators of multiple results to finally obtain a general classification.

So, we use six Type-1 fuzzy systems as integrators of each neural network's results by task. After, we use seven Interval Type-2 fuzzy systems as an integrator of the results of Type-1 fuzzy systems.

Finally, we use a General Type-2 fuzzy inference system which operates as the final Interval Type-2 FIS integrator of the results with the idea of achieving the best global result when compared to Type-1 and Interval Type-2 FIS results.

Both Type-1 and Type-2 fuzzy inference systems employed to aggregate the artificial neural networks are formed by two to three inputs and one output. They are Mamdani type, from nine to twenty-seven rules, and centroid defuzzification.

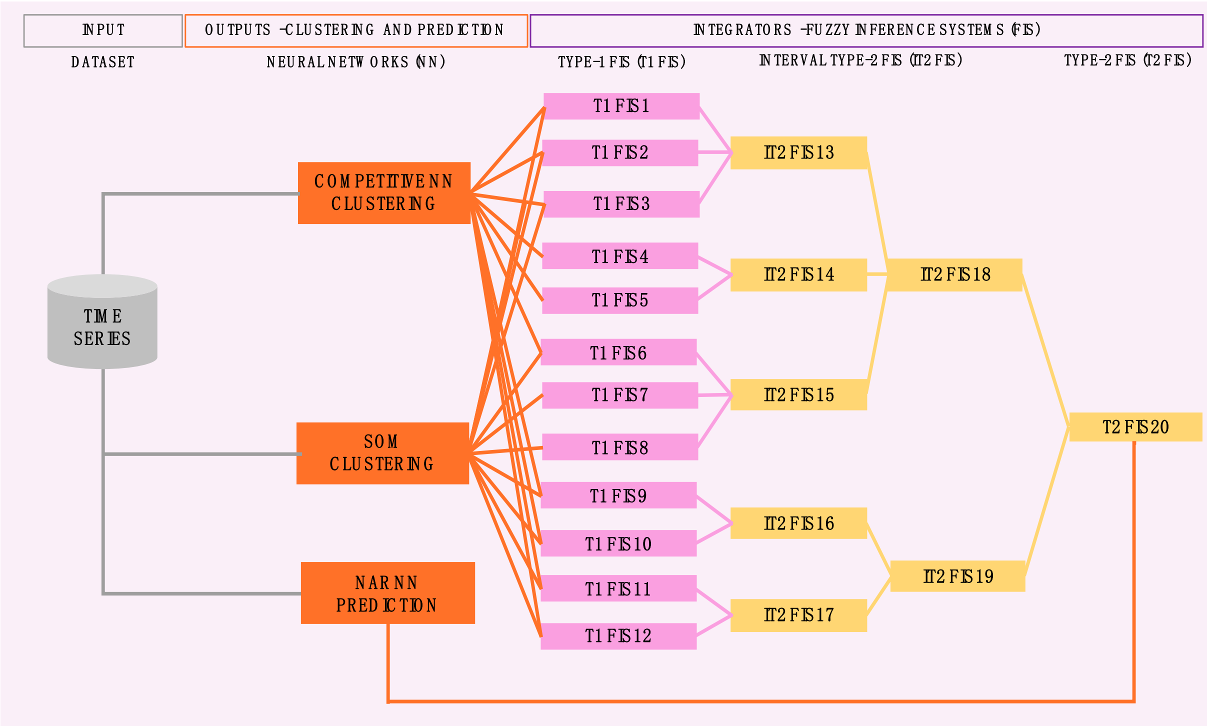

Figure 1. Proposed model.

For the Type-1, Interval Type-2, and General Type-2 fuzzy systems (Figure 2), the linguistic values of each variable are Low (LWW), Medium (MDD), and High (HGG).

The membership function (MF) parameters were manually obtained. The utilized MFs are Gaussian and triangular.

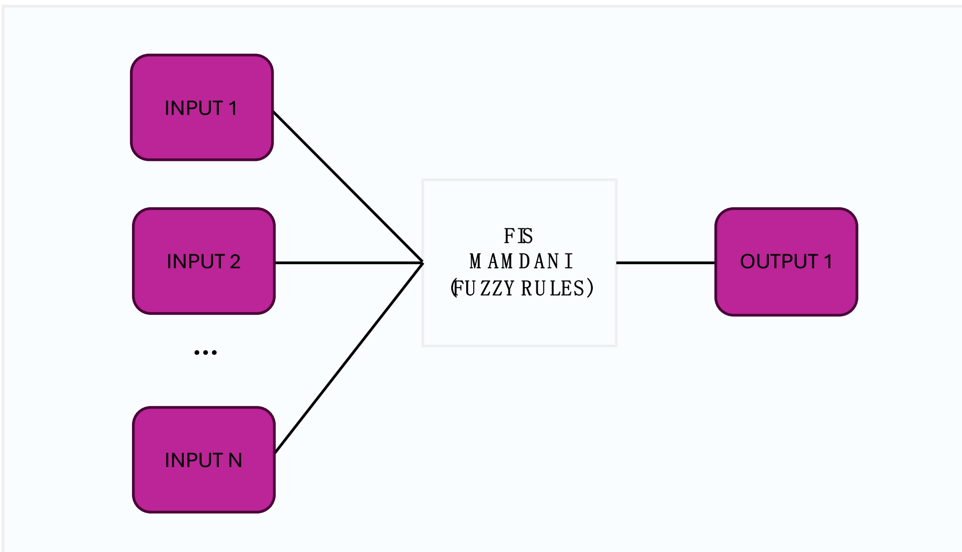

Figure 2. Fuzzy systems model.

In general, the fuzzy rules used are shown in Table 3 for the FIS with two inputs–one output, and in Table 4 for the FIS with three inputs–one output. Manual tests were carried out until this set of fuzzy rules was obtained.

Table 3. FIS Mamdani fuzzy rules (two inputs–one output).

Fuzzy Rules	Antecedents		Consequent
	Input_1	**Input_2**	**Output_1**
1	LWW	LWW	LWW
2	LWW	MDD	MDD
3	LWW	HGG	MDD
4	MDD	LWW	MDD
5	MDD	MDD	MDD
6	MDD	HGG	HGG
7	HGG	LWW	MDD
8	HGG	MDD	HGG
9	HGG	HGG	HGG

Table 4. FIS Mamdani fuzzy rules (three inputs–one output).

Fuzzy Rules	Antecedents			Consequent
	Input_1	**Input_2**	**Input_3**	**Output_1**
1	LWW	LWW	LWW	LWW
2	LWW	MDD	LWW	LWW
3	LWW	HGG	LWW	MDD
4	LWW	LWW	MDD	LWW
5	LWW	MDD	MDD	MDD
6	LWW	HGG	MDD	MDD
7	LWW	LWW	HGG	MDD
8	LWW	MDD	HGG	MDD
9	LWW	HGG	HGG	HGG
10	MDD	LWW	LWW	LWW
11	MDD	MDD	LWW	MDD
12	MDD	HGG	LWW	MDD
13	MDD	LWW	MDD	MDD
14	MDD	MDD	MDD	MDD
15	MDD	HGG	MDD	HGG
16	MDD	LWW	HGG	MDD
17	MDD	MDD	HGG	HGG
18	MDD	HGG	HGG	HGG
19	HGG	LWW	LWW	MDD
20	HGG	MDD	LWW	MDD
21	HGG	HGG	LWW	HGG
22	HGG	LWW	MDD	MDD
23	HGG	MDD	MDD	HGG
24	HGG	HGG	MDD	HGG
25	HGG	LWW	HGG	HGG
26	HGG	MDD	HGG	HGG
27	HGG	HGG	HGG	HGG

5. Experimental Results

In this work, we performed 30 executions for each NN. Firstly, we present the results obtained from the clustering carried out using competitive neural networks and, subsequently, the results obtained using a SOM for all the variables.

For all regions, results obtained by using competitive neural networks are shown in Table 5 and Figure 3, where the total countries by each class (RC1C, RC2C, RC3C, RC4C, RC5C, and RC6C) are described.

Table 5. Clustering of WDI time series by using competitive NN.

Variable	RC1C	RC2C	RC3C	RC4C	RC5C	RC6C
TSS1	15	111	18	33	14	17
TSS2	31	35	38	32	40	32
TSS3	25	36	38	40	38	31
TSS4	28	52	41	42	30	15
TSS5	29	39	41	25	40	34
TSS6	29	40	21	40	43	35
TSS7	36	36	37	33	36	30
TSS8	206	2	0	0	0	0
TSS9	196	10	2	0	0	0
TSS10	39	41	34	16	38	40
TSS11	206	2	0	0	0	0
TSS12	38	41	34	17	39	39

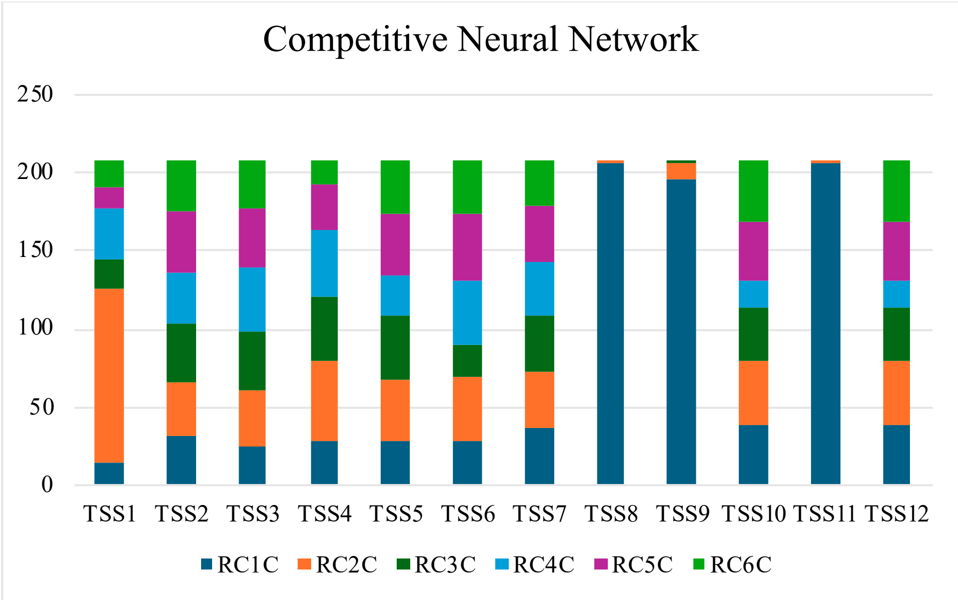

Figure 3. Clustering by using competitive NN (WDI time series).

Also, the results by the SOM are shown in Table 6 and Figure 4, where the total countries by each class (RC1S, RC2S, RC3S, RC4S, RC5S, and RC6S) are presented.

Table 6. Clustering of WDI time series by using SOM.

Variable	RC1S	RC2S	RC3S	RC4S	RC5S	RC6S
TSS1	18	112	21	22	17	18
TSS2	26	26	42	21	33	60
TSS3	2	16	68	22	64	36
TSS4	32	63	40	30	42	1
TSS5	27	50	66	25	39	1
TSS6	32	44	50	44	37	1
TSS7	60	57	28	57	5	1
TSS8	35	140	11	8	2	12
TSS9	37	147	7	2	14	1
TSS10	98	10	75	4	19	2
TSS11	33	140	13	8	2	12
TSS12	101	10	72	4	19	2

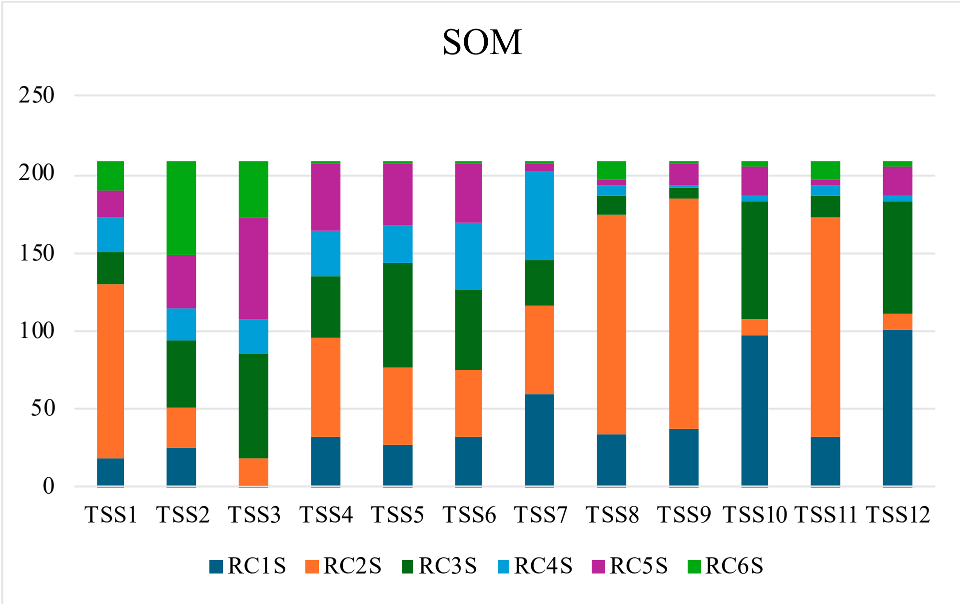

Figure 4. Clustering by using SOM (WDI time series).

In a similar way to the two previous figures corresponding to the clustering results, for each of the regions, the obtained results are shown below for illustrative purposes in Figures 5–7, where, for each of them, on the left side are the results of the competitive NN results and on the right side are those of the SOM. Also, the total number of countries corresponding to each class is visually indicated.

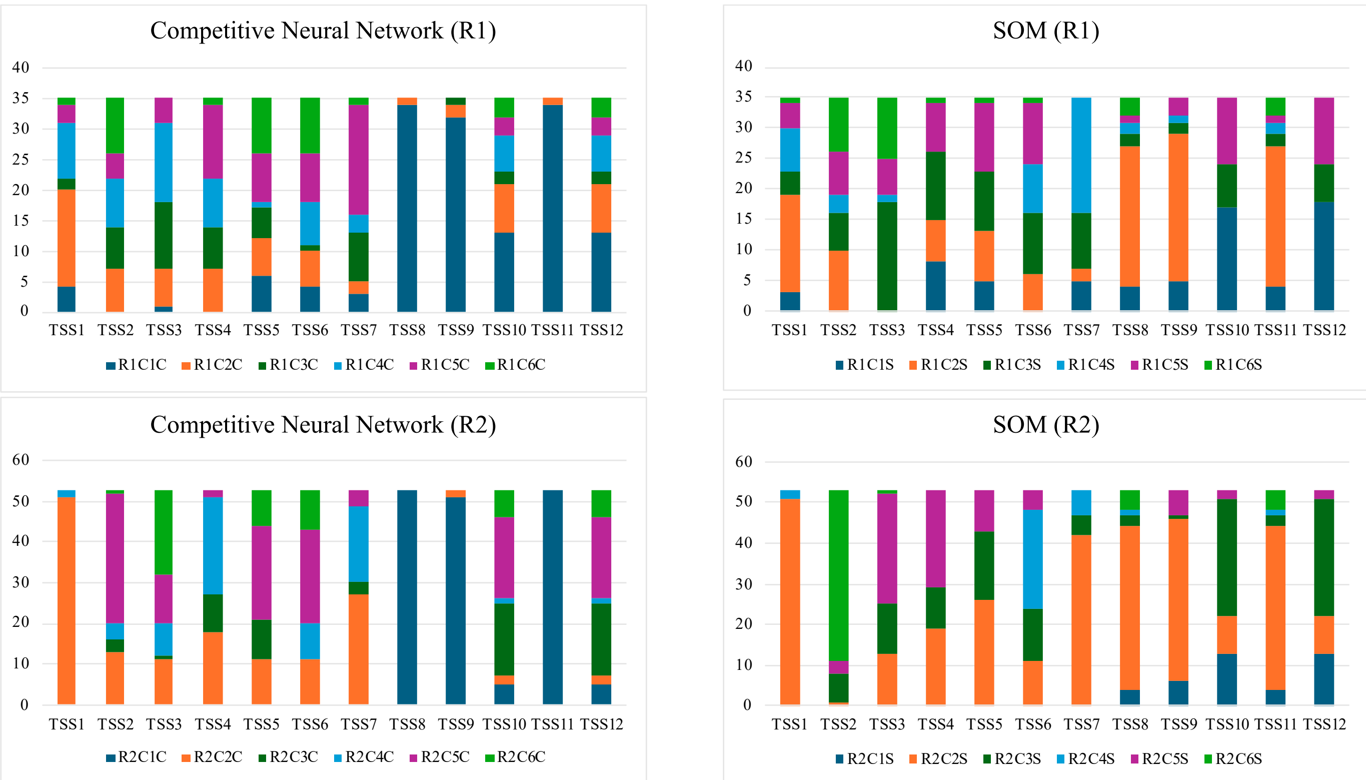

Figure 5. Clustering by using neural networks (R1 and R2).

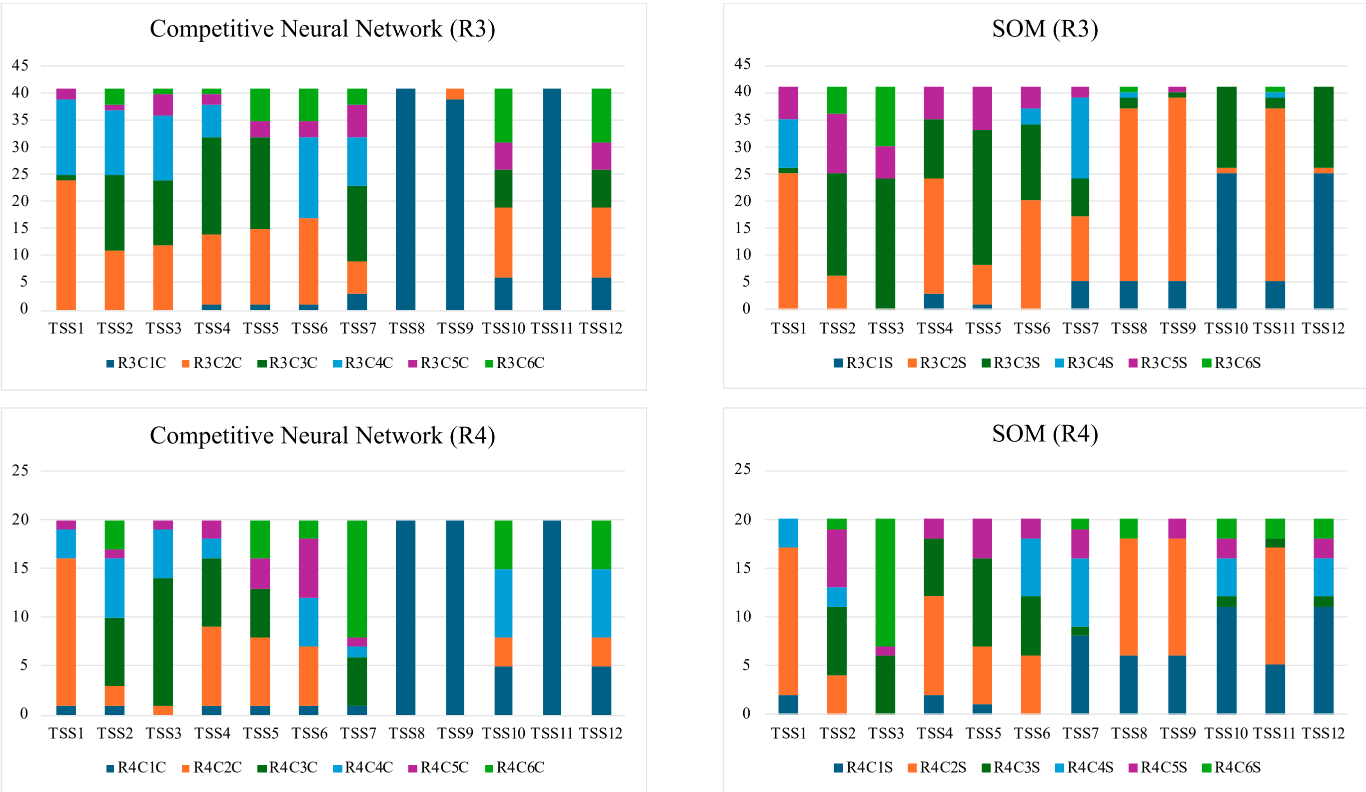

Figure 6. Clustering by using neural networks (R3 and R4).

With the results of the competitive neural networks and the SOM, we formed the two inputs of a Type-1 fuzzy system, where once these two results were integrated, the final class of each of the variables per country was obtained. The accumulated elements per region are presented in Table 7.

Table 7. Classification of WDI time series (Type-1 FIS).

FIS	**Type-1**											
Inputs	TSS1	TSS2	TSS3	TSS4	TSS5	TSS6	TSS7	TSS8	TSS9	TSS10	TSS11	TSS12
Outputs	T1	T1	T1	T1	T1	T1	T1	T1	T1	T1	T1	T1
(Subregion)	FIS1	FIS2	FIS3	FIS4	FIS5	FIS6	FIS7	FIS8	FIS9	FIS10	FIS11	FIS12
R1_R1	20	6	4	7	11	6	7	29	29	16	29	16
R1_R2	3	18	27	19	14	15	15	5	5	13	5	13
R1_R3	12	11	4	9	10	14	13	1	1	6	1	6
R2_R1	51	3	4	19	11	10	27	47	46	15	47	15
R2_R2	0	18	29	10	33	15	23	6	6	37	6	37
R2_R3	2	32	20	24	9	28	3	0	1	1	0	1
R3_R1	24	10	11	22	15	16	11	39	39	20	39	20
R3_R2	2	30	25	13	20	19	25	2	1	21	2	21
R3_R3	15	1	5	6	6	6	5	0	1	0	0	0
R4_R1	16	4	1	11	8	6	3	18	18	7	18	7
R4_R2	1	13	18	7	8	7	9	2	2	6	2	6
R4_R3	3	3	1	2	4	7	8	0	0	7	0	7
R5_R1	3	0	2	1	0	0	1	2	2	2	2	2
R5_R2	0	1	1	0	3	0	2	1	0	1	1	1
R5_R3	0	2	0	2	0	3	0	0	1	0	0	0
R6_R1	2	2	1	3	2	2	1	5	5	4	5	4
R6_R2	1	5	4	5	1	4	4	2	2	2	2	1
R6_R3	5	1	3	0	5	2	3	1	1	2	1	3
R7_R1	10	26	4	11	19	31	30	46	45	17	46	17
R7_R2	19	11	25	24	4	14	15	2	3	31	2	31
R7_R3	19	11	19	13	25	3	3	0	0	0	0	0

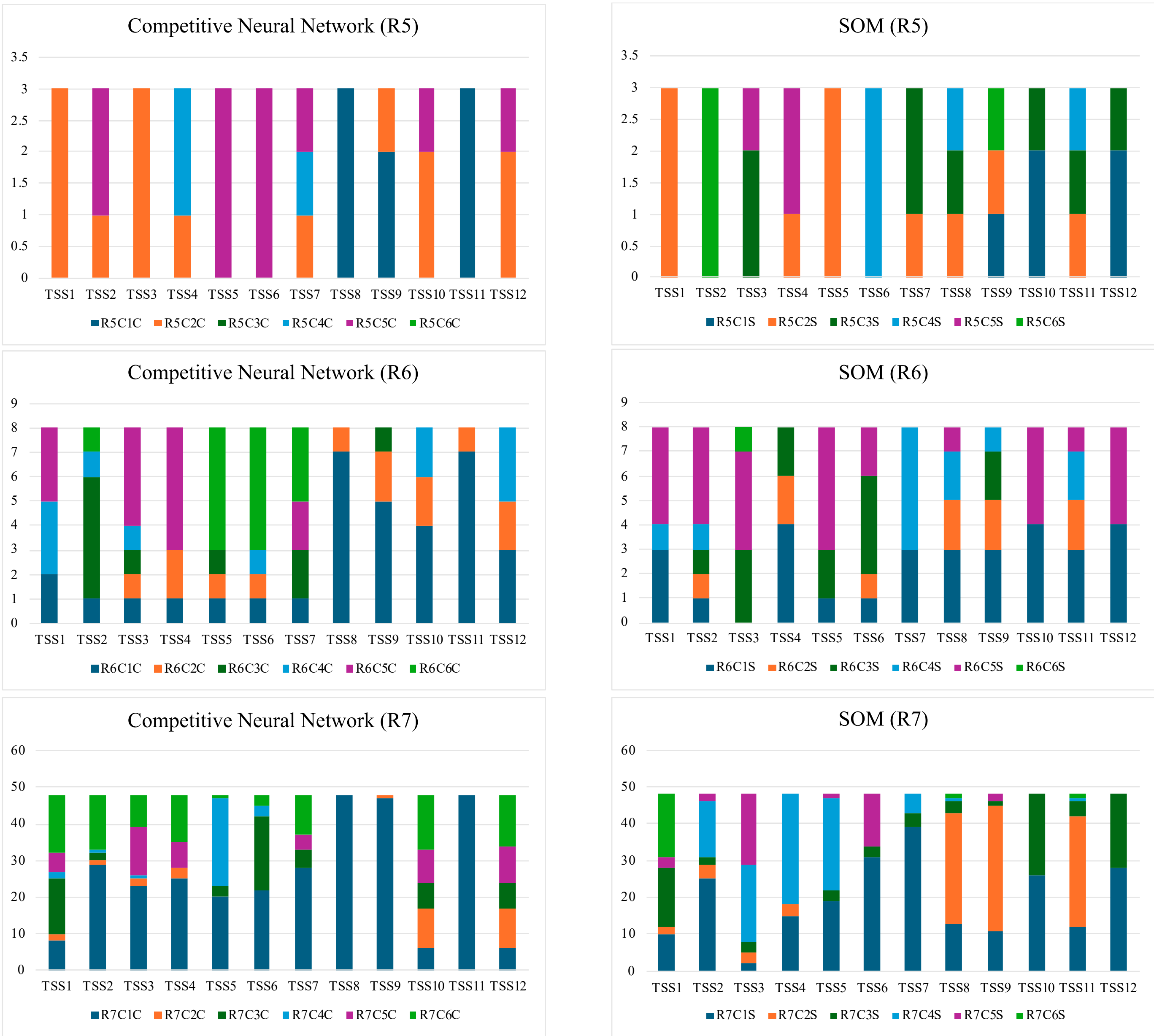

Figure 7. Clustering by using neural networks (R5, R6, and R7).

Now, with the purpose of integrating the 12 classes previously integrated with the Type-1 fuzzy systems into 5 classes, we prepared the inputs for 5 Type-1 fuzzy systems, where there were 2 to 3 inputs and 1 output, as shown in Table 8.

Afterward, we integrated the 12 classes previously integrated into 5 classes, but here we used 2 to 3 inputs and 1 output variable in an Interval Type-2 fuzzy system, as shown in Table 9.

Then, we integrated the five results obtained using two intervals and two Generalized Type-2 FIS, with the purpose of obtaining two criteria, as shown in Table 10.

Below, in Table 11, we present the comparison of the results obtained using the Type-1 FIS and Interval Type-2 FIS, where we noticed that for the five integrators when the Type-1 FIS was used, many countries were labeled with R3 compared to when we used the Interval Type-2 FIS.

Table 8. Classification of WDI time series (Type-1 FIS) for 12 classes.

FIS	Type-1				
Inputs	T1 FIS1 T1 FIS7 T1 FIS8	T1 FIS2 T1 FIS3	T1 FIS4 T1 FIS5 T1 FIS6	T1 FIS9 T1 FIS11	T1 FIS10 T1 FIS12
Outputs (Subregion)	T1_IR1	T1_IR2	T1_IR3	T1_IR4	T1_IR5
R1_R1	0	0	0	0	0
R1_R2	6	0	0	2	0
R1_R3	29	35	35	33	35
R2_R1	0	0	0	0	0
R2_R2	4	0	0	2	0
R2_R3	49	53	53	51	53
R3_R1	0	0	0	0	0
R3_R2	7	0	1	2	0
R3_R3	34	41	40	39	41
R4_R1	1	0	0	0	0
R4_R2	3	0	1	1	0
R4_R3	16	20	19	19	20
R5_R1	0	0	0	0	0
R5_R2	0	0	0	1	0
R5_R3	3	3	3	2	3
R6_R1	1	0	1	0	0
R6_R2	0	0	0	0	0
R6_R3	7	8	7	8	8
R7_R1	4	0	6	0	0
R7_R2	13	4	6	3	0
R7_R3	31	44	36	45	48

Table 9. Classification of WDI time series (Interval Type-2 FIS).

FIS	Interval Type-2				
Inputs	T1 FIS1 T1 FIS7 T1 FIS8	T1 FIS2 T1 FIS3	T1 FIS4 T1 FIS5 T1 FIS6	T1 FIS9 T1 FIS11	T1 FIS10 T1 FIS12
Outputs (Subregion)	IT2_IR1	IT2_IR2	IT2_IR3	IT2_IR4	IT2_IR5
R1_R1	0	0	0	0	0
R1_R2	21	31	6	11	21
R1_R3	14	4	29	24	14
R2_R1	0	0	0	0	0
R2_R2	49	34	11	13	41
R2_R3	4	19	42	40	12
R3_R1	0	0	1	0	0
R3_R2	25	37	16	9	27
R3_R3	16	4	24	32	14
R4_R1	1	0	1	0	0
R4_R2	12	19	8	8	10
R4_R3	7	1	11	12	10
R5_R1	0	0	0	0	0
R5_R2	2	1	0	2	1
R5_R3	1	2	3	1	2
R6_R1	1	0	1	0	0
R6_R2	0	6	1	5	4
R6_R3	7	2	6	3	4
R7_R1	7	0	12	0	0
R7_R2	16	38	1	18	37
R7_R3	25	10	35	30	11

Table 10. Classification of WDI time series (Type-2 FIS).

FIS	Interval Type-2	Interval Type-2	Interval Type-2	Generalized Type-2
Inputs	T1_IR1 T1_IR2	T1_IR3 T1_IR4 T1_IR5	IT2_R1 IT2_R2	IT2_R1 IT2_R2
Outputs (Subregion)	IT2_R1	IT2_R2	IT2_RG	T2_RG
R1_R1	0	1	2	1
R1_R2	35	33	33	33
R1_R3	0	1	0	1
R2_R1	0	0	3	0
R2_R2	53	53	50	53
R2_R3	0	0	0	0
R3_R1	0	0	3	0
R3_R2	41	41	38	41
R3_R3	0	0	0	0
R4_R1	1	2	2	1
R4_R2	18	18	18	18
R4_R3	1	0	0	1
R5_R1	0	0	0	0
R5_R2	3	3	3	3
R5_R3	0	0	0	0
R6_R1	1	1	1	1
R6_R2	7	7	7	7
R6_R3	0	0	0	0
R7_R1	10	9	5	8
R7_R2	34	39	43	37
R7_R3	4	0	0	3

Table 11. Comparison of Type-1 and Type-2 FIS.

FIS	Type-1 (T1)/Interval Type-2 (IT2)									
Inputs	T1 FIS1 T1 FIS7 T1 FIS8		T1 FIS2 T1 FIS3		T1 FIS4 T1 FIS5 T1 FIS6		T1 FIS9 T1 FIS11		T1 FIS10 T1 FIS12	
Outputs (Regions)	T1_IR1	IT2_IR1	T1_IR2	IT2_IR2	T1_IR3	IT2_IR3	T1_IR4	IT2_IR4	T1_IR5	IT2_IR5
R1	6	9	0	0	7	15	0	0	0	0
R2	33	125	4	166	8	43	11	66	0	141
R3	169	74	204	42	193	150	197	142	208	67

So, it was possible to obtain a better classification of the regions by separating the countries belonging to R2 and, also for the integrators IT2_R1 and IT2_R3, the number of countries corresponding to R1 increased.

In Table 12, we summarize the comparison of results with the use of the Interval Type-2 FIS and a Generalized Type-2 FIS. We noticed that better results were obtained by using the Generalized Type-2 FIS since it was possible to obtain countries belonging to R3 and vary the number of elements belonging to R1 and R2, compared to the Interval Type-2 FIS.

In the case of supervised neural networks, because good results were obtained in previous experimentation, we divided the original sequence of the time series into 70% of the dataset for training, 15% for validation, and 15% for testing.

It should be noted that the sequential order of each time series remained. Also, the relative percentage of Root Mean Square Error (%RMSE) was used to measure the prediction performance of each NN.

Table 12. Comparison of results of Type-2 FISs.

FIS	Interval Type-2	Generalized Type-2
Inputs	IT2_R1 IT2_R2	IT2_R1 IT2_R2
Outputs (Regions)	IT2_RG	T2_RG
R1	16	12
R2	192	191
R3	0	5

The results of the prediction of the future values of each variable were obtained using a NAR neural network and are shown below in Table 13.

Table 13. Prediction of WDI time series (NAR).

Variable	Average %RMSE	Best %RMSE	Worst %RMSE
TSS1	0.000027798	0.000013944	0.000048778
TSS2	0.000026712	0.000014912	0.000043324
TSS3	0.000064301	0.000038295	0.000111326
TSS4	0.000016197	0.000008287	0.000030772
TSS5	0.000012526	0.000006770	0.000020071
TSS6	0.000014930	0.000008680	0.000028881
TSS7	0.000134383	0.000084544	0.000201535
TSS8	0.000105706	0.000022670	0.000287229
TSS9	0.000091964	0.000025740	0.000286967
TSS10	0.000002059	0.000001169	0.000003839
TSS11	0.000110160	0.000024207	0.000252354
TSS12	0.000002194	0.000001190	0.000003500

We separated the data corresponding to R1 classified using the Generalized Type-2 fuzzy system, and the results of the prediction of the future values of each variable were obtained using a NAR neural network, as shown in Table 14.

Table 14. Prediction of WDI time series by class R1_T2_RG (NAR).

Variable	Average %RMSE	Best %RMSE	Worst %RMSE
TSS1	0.000420807	0.000092340	0.000949776
TSS2	0.000130195	0.000052815	0.000245523
TSS3	0.000332452	0.000167022	0.000591463
TSS4	0.000066602	0.000019978	0.000165994
TSS5	0.000137332	0.000070974	0.000296870
TSS6	0.000146327	0.000071138	0.000393558
TSS7	0.001108667	0.000573669	0.002632906
TSS8	0.000886138	0.000215622	0.002840459
TSS9	0.000851274	0.000180802	0.003587455
TSS10	0.000004522	0.000002657	0.000008226
TSS11	0.000960787	0.000170907	0.002616553
TSS12	0.000005042	0.000002598	0.000007630

6. Discussion of Results

We should highlight that by combining intelligent methods, it is possible to focus on using an unsupervised model as the first phase to identify similarities or patterns in the data, seeking to highlight key variables and as a second phase focus on predicting the future values of these variables, as well as focusing on the segments of an attribute for a given range, period, or geographic location.

Clustering results were obtained to form six groups or classes using two types of unsupervised neural networks, which showed slight differences in the groups formed.

A Type-1 fuzzy integration was used to obtain a final label or class, based on the results mentioned above.

We also note that one of the advantages of the method is that it is possible to combine artificial neural network models and use sets of fuzzy systems to perform classification, clustering, and prediction. By working or forming segments of information grouped by similar attributes, it allows us to obtain specific results for one or multiple variables. In addition, our model contemplates uncertainty management for decision making and the integration of results through several fuzzy systems.

We conclude that the results show that it is possible to use General and Interval Type-2 fuzzy systems to integrate country indicators in a better way than with Type-1 fuzzy systems. This is because in these types of systems, the coverage of the membership functions considers to a greater extent the crossing of the lower and upper limits of each indicator, so the proximity to the next range or class is considered at the time of integration of the linguistic values. In other words, these Type-2 FIS can better manage the implicit uncertainty in the historical values of the selected sample of countries.

7. Conclusions

Simulation results demonstrate that it is possible to use General Type-2 fuzzy systems to integrate the obtained results through neural networks or create nested structures of fuzzy systems to perform a level integration. Moreover, the Interval Type-2 fuzzy systems presented good results when considering two or more variables in comparison with Type-1 fuzzy systems.

Then, it was shown that General Type-2 fuzzy systems presented better results than Interval Type-2 and Type-1 fuzzy systems when they acted as integrators of results.

Also, we observe that by using multiple Type-1 and Type-2 fuzzy systems it is possible to classify countries or indicators and it is also possible to integrate the obtained results using neural networks, always aiming to serve as a support tool in decision making.

As future work, we first consider selecting global datasets consisting of well-being indicators, both qualitative and quantitative, to perform tests of multiple fuzzy integration techniques. We also contemplate developing new case studies that consider optimization methods applied to fuzzy systems, particularly to optimize fuzzy rules and membership function parameters. It is also intended to enhance prediction results by employing intelligent hybrid techniques to perform classification and prediction tests.

In addition to the last point, we are hoping that by separating the information used by organizations based on the responsibilities of the people or areas involved in the preparation of reports for decision making, we can prevent or reduce the risk of significant weaknesses or deficiencies in the relevant processes.

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