Level of Vulnerability of Educational Institutions in Face El Niño Phenomenon and its Classification with the Neural Network

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***Summary*— The El Niño Phenomenon is a climatic event whose consequences are devastating for Peru (Landslides, floods, etc). Due to this, in the present investigation a neural network is proposed, this RNA has the capacity to evaluate the level of vulnerability before this event of a building, more specifically, an educational institution. An artificial multi-layer perceptron neural network was developed, trained with the backpropagation algorithm. This training was carried out using the results of the risk level assessment developed by the Ministry of Agriculture and Irrigation of Peru, approximately twelve thousand records were used. He developed two types of architectures with different number of neurons in the hidden layer. Finally, the first architecture was selected as the most suitable because it had a root error of 0.05, being less than the second architecture. With the training obtained in the first neuron, a web application was implemented to classify the level of vulnerability of an educational institution according to certain patterns present in it.**

I. INTRODUCTION

The El Niño Phenomenon is the generalized increase in the temperature of the sea surface in a large part of the Eastern and Central Equatorial Pacific sector [1]. It is also defined as a cyclical climatic phenomenon that causes havoc worldwide, being the most affected South America and the areas between Indonesia and Australia, causing the warming of South American waters [2].

Some problems that are seen are: Increase in the temperature of the Peruvian marine surface, increase in air temperature in coastal areas, decrease in marine outcrop, Excessive rains on the north coast, causing floods and river overflows and alteration of marine and coastal ecosystems.

The aforementioned characteristics of the El Niño Phenomenon, especially floods and overflows, destructively affect the buildings that are in its path [3]. Being one of these educational institutions, which are the focus of the present study.

The last Phenomenon of the Child, which occurred in Peru, was developed in the year 2017 between the months of January and April leaving a balance of 354 educational institutions destroyed and 3266 affected. Among other affected buildings there were 6,6093 homes destroyed and 64 unserviceable health facilities. The number of people killed was 162, the injured were counted to 500 and the disappeared reached the figure of 19 [4].

The Peruvian coast is considered the most vulnerable region to the effects of the El Niño phenomenon, this is due to several factors: The Peruvian coast is arid, the riverbeds that are normally dry accumulate a lot of material, such as stones and even garbage, and when it rains, landslides are generated [6]. Another factor is the lack of vegetation in the mountains, since it fixes the ground and prevents displacement when it rains. Finally, the lack of urban planning is an important cause of risks, because people settle in areas with high vulnerability to floods or landslides caused by the El Niño Phenomenon [5].

It is possible to determine the level of risk of the constructions in the face of the threat of damage caused by the El Niño phenomenon, the level of infrastructure of the building, the type of soil where it is located, the type of hydrographic area which can be specified. surrounds All these factors can be taken and evaluated to determine the level of vulnerability to the effects of the El Niño Phenomenon [6].

The aim of this research is to determine the level of vulnerability of an educational institution before the effects of the El Niño phenomenon using a classification algorithm (Neural Networks). The data for the training of the network are based on an evaluation carried out by the Ministry of Education of Peru (MINEDU) [7] which determines the level of vulnerability of educational institutions according to a score obtained.

II. STATE OF THE ART

A study developed by the Sepuluh Nopember Institute of Technology evaluated the vulnerability level of buildings against earthquakes in Indonesia, using the PushOver analysis. This analysis allows to determine the behavior of a construction before an earthquake. The reason for the aforementioned research is to provide a classification of the vulnerability of buildings to an earthquake, these classifications are determined by a score range from 0 to 25, which is obtained after conducting the vulnerability assessment. The categories of risk provided are: light damage (0% to 30%), moderate damage (30% to 70%) and severe damage (70% to 100%) [8].

Another study developed by the MIT College of Engineering in India, proposes a flood prediction analysis system, which uses Neural Networks and the Internet of Things. The system uses different sensors to obtain data such as humidity, atmospheric pressure, temperature, etc. These data are sent through microcontrollers to a neural network so that the risk of an imminent flood is determined, once the risk is determined, a message is sent to the people who are in the area that is going to be affected. In the training of the neural network a data set corresponding to the 2015 floods in the Chennai region was used. The data set contained 176 records, of which 70% was used for training the neural network, 15% for validation and 15% for testing. The topology of the neural network is a NARX network, which is a type of network with feedback mainly applied to nonlinear dynamic systems such as time series predictions. The finished system is capable of alerting people who are in the risk area to an imminent flood threat [9].

In the Geographical Research department of the Autonomous University of Mexico, social vulnerability to natural hazards is understood as the specific level of exposure and fragility suffered by human groups settled in a place before certain dangerous events, depending on a set of factors socio-economic, institutional, psychological and cultural [14]. The main problems of social vulnerability to natural disasters are socioeconomic status, age, employment and gender, degree of environmental development.

One of the methodologies used is the qualitative ACP and its process, a multivariate analysis technique, which aims to generate new variables that can express the information contained in the original data set, reduce the dimensionality of the problem being studied and eliminate the original variables if they provide information.

The assessment of vulnerability, the upper, middle and lower classes, define intervals and ranges for the different levels of vulnerability in a study area. In conclusion, the methodology allows establishing the correlation between the socioeconomic conditions of the inhabitants and their levels of exposure to natural hazards [10].

A study by the Chinese Medical Research Institute emphasizes the role of the vulnerability assessment (HVA) for disaster prevention and mitigation and proposes a framework for the creation of a HVA China, with its 1,300 million inhabitants, is prone to social disasters, such as the collapse of the Eastern Star due to a cyclone. The yacht carried 450 people and they were only rescued 8 [13]. Three of the 10 most fatal earthquakes have occurred in China [15], in the years 1556 in Shaanxi, 1976 in Tangshan, and in 1920 in Haiyuan. This, together with the great Chinese population density (145 inhabitants / km2), lack of disaster response plans only increases vulnerability. To develop an adequate HVA, the study considers 3 main factors for the preparation of an adequate HVA: the constitution of a HVA team in the communities and develop the content of the HVA including the most probable vulnerabilities in the region [13], and concludes that a standardized and comprehensive HVA can help health institutions and communities prepare for and improve disaster response.

The framework presented in [13] is very useful to improve the preparedness of the population before an event post-desastre, pero la predicción resulta más útil in specific disasters such as natural disasters, as proposed in [16]. A. Joko et al. propose a system based on a Learning Vector Quantization (LVQ) neural network, which has a higher performance on the back-propagation method [17] to predict natural disasters. The biggest problem is the processing of satellite images because they are very heavy, and they propose a compression method using wavelet transform. 8 wavelets are used, among which are: Haar, Coiflet1, Coiflet 3, Symlet2, Symlet5, 1AJS, AJS2 and AJS3. As a sample of images, tornado and hurricane sequences are taken, obtaining a compression ratio of 99.25% with Haar for tornadoes and 98.43% with Symlet2 for hurricanes, to finally conclude that to minimize the time in the learning process from the neural network you can preprocess the images using wavelets.

Both the work investigations [8] and the work [9] focus on evaluating patterns that indicate the level of risk in a disaster (flood in this case). However, the work [9] offers a greater scope, because the proposed system acts in real time, this capacity is due to the use of IoT, which is composed of sensors able to collect input data in real time and be sent to a neural network for immediate classification. In the same way, studies [13] and [16] complement each other to offer a more effective system for the elimination of vulnerabilities, the first presents a disaster response and prevention framework, and the second allows disaster prediction of natural type.

III. Architecture Design

A neural network of classification will be developed to fulfill the objective of the study, which is a classifier of vulnerability level of educational institutions before the El Niño Phenomenon.

A. *Obtaining the data*

The first step was the construction of the data source to train the neural network. The number of records obtained is 19,879 in total.

The data was obtained from the database of the Ministry of Education of Peru (MINEDU), which was updated for the last time in 2016. The privacy policy of said Database is public. These data are the result of an evaluation carried out by MINEDU itself, which covers the type of area, flood risk, landslide, mass movement, infrastructure, etc.

Finally, an Excel document was created, which groups all the data obtained.

TABLE I. Input Variables

Variable	Description	Values
Area	Type of area where the educational institution is located	0 = Urban 1 = Rural
R_Des	Risk of landslide	1 = Very Low 2 = Low 3 = Regular 4 = High 5 = Very High
R_Inund	Risk assessed by MINAM (Ministry of the Environment of Peru)	1 = Yes 0 = No

R_Mov_Mas	Risk of Mass Movement	1 = Very Low 2 = Low 3 = Regular 4 = High 5 = Very High
R_Inund_INGEMMET	Flood Risk evaluated by INGEMMET (Geological, Mining and Metallurgical Institute)	1 = Very Low 2 = Low 3 = Regular 4 = High 5 = Very High
Infra_N1	Very bad infrastructure	1 = Yes 0 = No
Infra_N2	Bad infrastructure	1 = Yes 0 = No
Infra_N3	Fair or good infrastructure	1 = Yes 0 = No

B. Training of the Neural Network

To train the neural network Perceptron with retro propagation we proceed to enter a set of training data p_k. looking for a response from the network, which approaches a value T_k established. This training consists in taking the data entered by the user and activating the neural network with initial weights generated in a random way. The network will propagate these inputs through the layers, each neuron will have an input weight and an output weight, when the inputs pass through all the neurons, it will generate a pair of values in the last layer, in general if the expected response from the network is T = (T1, T2, ..., Tn) ∈ Rn, for a set of data that is supplied for P = (p1, p2, ..., pn). Then the network will change its weight to deliver an answer R = (R1, R1, ..., Rn), which approaches T = (T1, T2, ..., Tn).

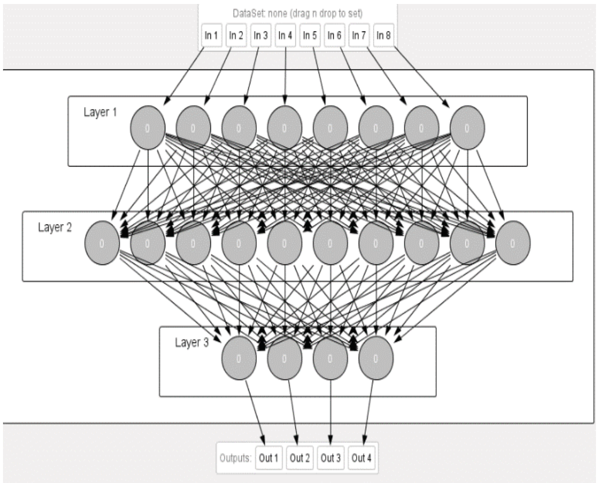

Fig. 1. Structure of a Multilayer Perceptron

To use the retro-propagation algorithm, we calculate the output of the network, then we calculate the difference between the actual output of the network and the desired output, with which we obtain the error vector. Then we adjust the weights of the network so that the error is minimized, then repeat the previous three steps for each training pair until the error for all the training sets is acceptable.

The network construction starts with weights and thresholds (-0.5, 0.5), then the termination criterion with an iteration counter n = 0. In the forward phase, the output of the network is calculated each input pattern, which is to calculate the total error committed (SSE) if the condition is satisfied, the algorithm is stopped.

C. Level of Vulnerability

When a pattern is entered (a record composed of the values indicated in Table I) the network interprets this as an entry. These inputs have a set of characteristics that was designated as a pattern, once a group of the employer has been entered, the network uses the training learned for this purpose. can give a set of results, these results are a certain classification to indicate the level of vulnerability.

D. Interpretation of results generated by neural networks

The system takes the results generated by the neural network to be able to interpret them, with the data obtained it is directed towards the Excel template where a table contains the interpretations, Table II shows the interpretations of the possible results of the neural networks. Where the classification determined by the previously trained neural network is specified.

TABLE II. OUTPUT VARIABLES

Output Name	Description	Output
S_1	Very High	0= No 1=Si
S_2	High	0= No 1=Si
S_3	Medium	0= No 1=Si
S_4	Low	0= No 1=Si

IV. APPLICATION DESIGN

The training of the neural network developed through a Web application, programmed in JavaScript, will be tested. The objective of this application is to show a form composed of the characteristics of an Educational Institution in Peru.

A. Functional Requirements

The first requirement is to record the user's inputs (Data conformed by the values in Table I), the second requirement is to classify the level of vulnerability of the educational institution.

B. System actors

Any system entity that interacts with the vulnerability classification system is defined as the system actor, Table III shows the system's actors.

TABLE III. USER PROFILE

Actor	Description
Administrator	Person in charge of maintaining the platform, has all the accesses.
Coach	Person in charge of training the developed neural network.
Consultant	Person who makes the query to the neural network to determine the level of vulnerability of the institutions.

C. Processes

According to the data entered in the aforementioned form, the result of the classification of the trained neural network will be shown.

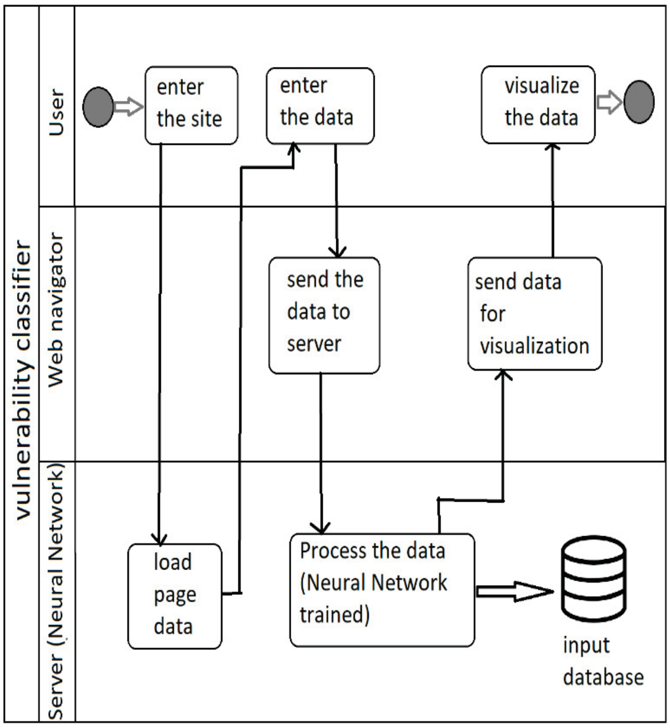

Fig 2. Flow of Use of the Web Application

D. Telefónica Open Cloud

• Telefónica Open Cloud is a public cloud provider, based on open source technologies, it offers computing, storage, networking and security services. In partnership with Huawei Technologies Co., Ltd., it offers public cloud throughout Latin America. The solution has local data centers in each country present. This solution was chosen due to the ease of access to the cloud thanks to our collaborators working in Huawei del Peru S.A.C [19].

E. Telefónica Open Cloud

- Data access layer: This layer contains the database to be used, which is MongoDB. This database has been chosen for the simplicity and speed provided, since only one table will be used for the storage of the input data
- Business layer: In this layer the node.js technologies will be used for the server. This environment has been chosen because it integrates very well with very small load servers, consuming a minimum of resources. In this layer the logic of the neural network will be housed.
- Presentation layer: in this layer Angular will be used, and this technology has been chosen since its integration with node.js is native, by using both the Javascript programming languages. In this layer the userwillenterthe input data.

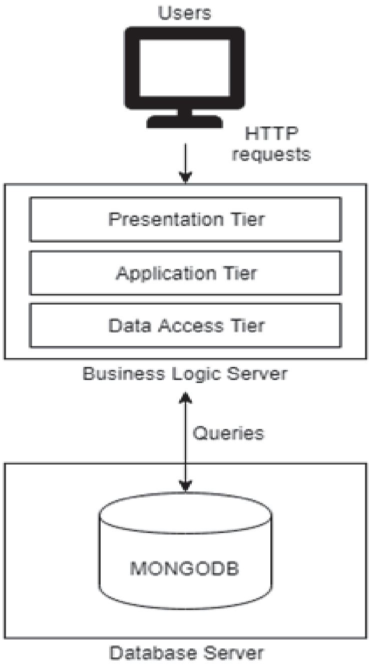

Fig. 3. Architecture of the web application

V. Results and Discussion

This part shows the results of the training of 2 different architectures for the neural network (Multilayer Perceptron). The selected tool to perform the exploration and experimentation is Neurosoph Studio. Which is a JavFrame Work to develop neural network architectures.

The treated dataset was divided into two parts: 70% for training and 30% for testing. With a hidden layer of 10 neurons and Bias.

We design the architecture A, with 8 inputs and one of bias, 4 outputs and 10 neurons in the hidden layer (plus the bias).

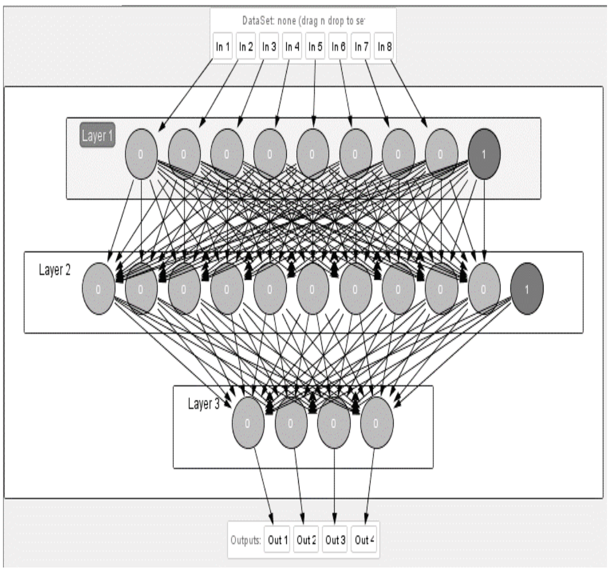

Fig. 4. Architecture of the Neural Network A

A where the corresponding entries are indicated in Table I and outputs in Table II.

The network trained for 5 epochs with a learning factor of 0.2 and a momentum of 0.7.

Fig. 5 shows the total error graph of the neural network during training. A final error of less than 0.01 and a quadratic error of 0.0506 was obtained.

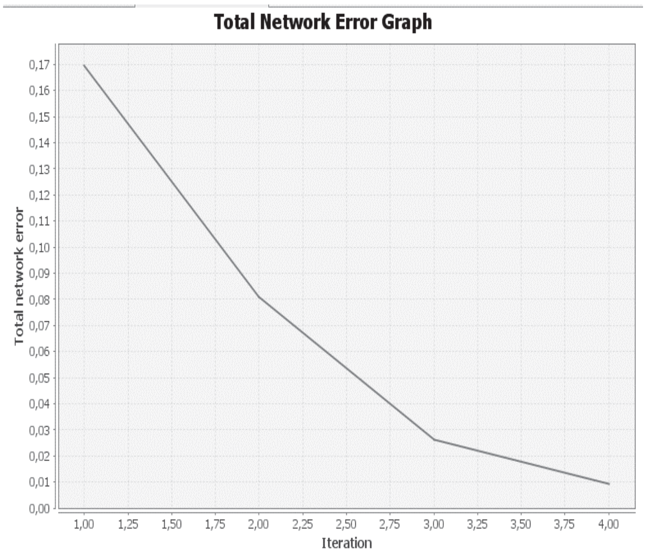

Fig. 5. Total Error Graph of Network A

The test was performed using data corresponding to the test data set this is one of the cases.

TABLE IV. INPUT DATA TO ARCHITECTURE A

Variable	Values	Input
Área	0	In1
R_Des	4	In2
R_Inund	1	In3
R_Mov_Mas	3	In4
R_Inund_INGEMMET	3	In5
Infra_N1	0	In6
Infra_N2	0	In7
Infra_N3	1	In8

Expected output

TABLE V. EXPECTED OUTPUT A

S_1	S_2	S_3	S_4
0	**1**	0	0

TABLE VI. OUTPUT TABLE OBTAINED FOR A

S_1	S_2	S_3	S_4
0.025	**0.97**	0.05	0

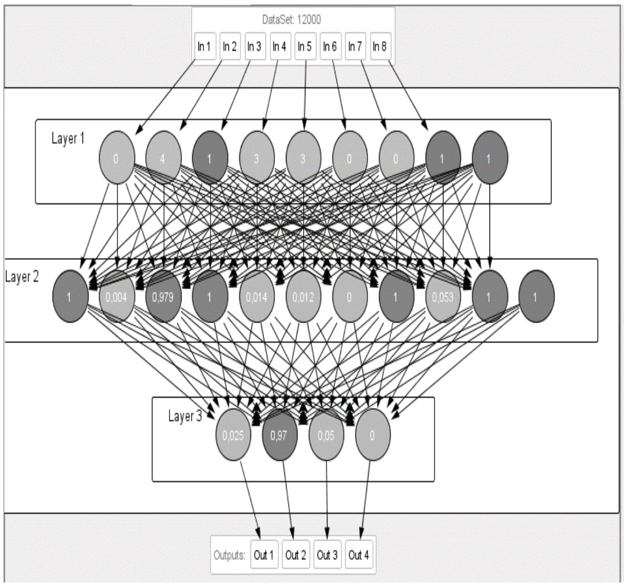

Fig. 6. Viewing prediction values for architecture A

Finally for architecture A, the same way it has been tested with 30% of test data obtaining accuracy 92.50%.

Another architecture we have proposed, with a hidden layer of four neurons, an architecture with 8 inputs and one of bias, 4 outputs and 4 neurons in the hidden layer (plus the bias) was proposed.

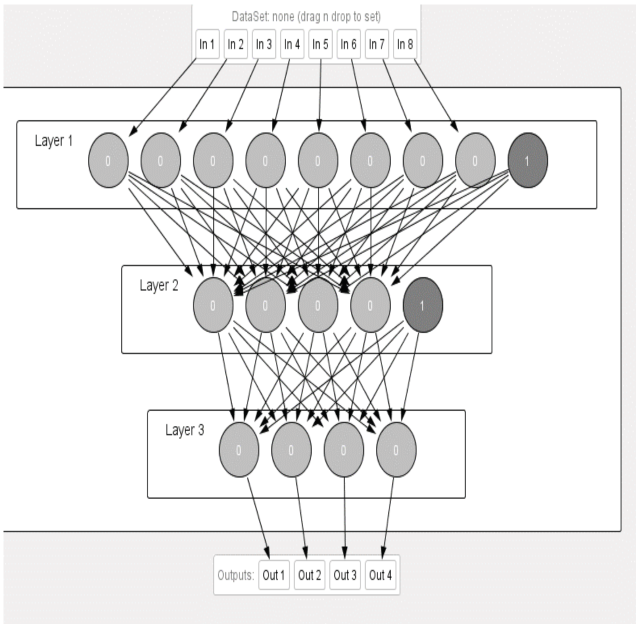

Fig. 7: Architecture of the Neural Network B

Where the corresponding entries are indicated in Table I and outputs in Table II.

The network trained for 5 epochs with a learning factor of 0.2 and a momentum of 0.7.

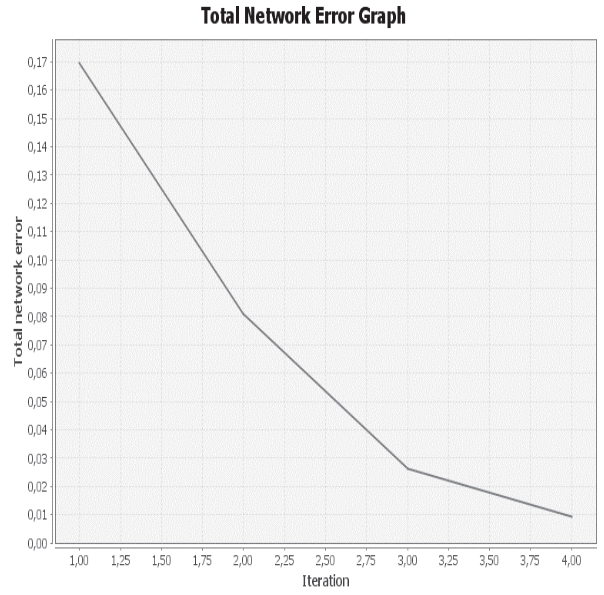

Fig. 8: Graph of the network in the T2 test

The test was performed using data corresponding to the test data set this is one of the cases.

TABLE VII. INPUT DATA TO ARCHITECTURE B

Variable	Values	Input
Área	1	In1
R_Des	5	In2
R_Inund	0	In3
R_Mov_Mas	4	In4
R_Inund_INGEMMET	1	In5
Infra_N1	0	In6
Infra_N2	1	In7
Infra_N3	0	In8

Expected output

TABLE VIII. EXPECTED OUTPUT B

S_1	S_2	S_3	S_4
1	**0**	0	0

TABLE IX. OUTPUT TABLE OBTAINED FOR B

S_1	S_2	S_3	S_4
0.977	0.019	0.01	0

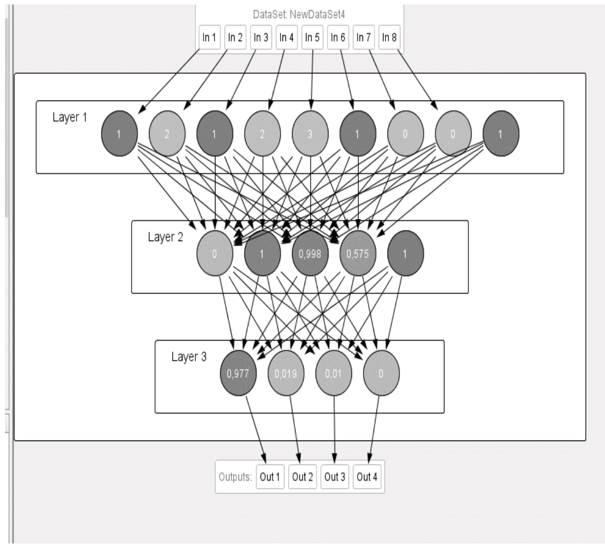

Fig. 9: Viewing Prediction Values for Architecture B

Finally for architecture B, the same way it has been tested with 30% of test data obtaining accuracy 95.20%.

After experimenting with the two architectures, architecture B is the best with 95.20% accuracy that allows predicting the level of vulnerability of educational institutions.

Unlike the network developed in article [8], which classifies the level of vulnerability of a construction in three levels, the network presented in this work classified into 4 levels, the latter being more specific at the time of vulnerability assessment.

In the case of the network developed in article [9], its operation is performed through distributed systems, that is, it receives data sent from sensors located in different environments, the network presented in this work only enters information through an application Web. Requiring only the data necessary for the evaluation of the vulnerability.

In contrast to the study presented in the article [14] which takes characteristics of the socioeconomic type, the present study is limited to evaluating data of the geographical type (Flood Risk, landslides, etc.).

Similarly, to the paper [13], the HVA also evaluates the level of vulnerability of natural disasters associated with floods, which are frequent episodes in the region studied (China). Comparing with our work, we were able to predict the level of vulnerability of educational institutions using neural networks.

CONCLUSIONS AND FUTURE WORK

We design and determine the best neural network architecture to predict the level of vulnerability of educational institutions, we also propose an application for educational institutions that want to see the prediction of the risk they have according to their characteristics. In the future, it is intended to work on the level of vulnerability in cities in the face of natural phenomena.

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