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Detection and Risk Level of COVID 19 through Artificial Neural Networks

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Abstract

Around March 2020, the UN declared the coronavirus COVID-19 disease outbreak as a pandemic. The cases registered worldwide from the beginning and until February 2023 ascend to a total of 755 million, and a total of 6.8 million deaths. There are various levels of progress in the transmission of COVID-19, which can be from a mild to moderate transmission, or from a serious state to a critical state presenting severe acute respiratory syndrome (SARS). For this reason, it is extremely important to detect in time whether a person is suffering from COVID-

19 based on the symptoms they present, and if the patient is a positive case, it is important to know if they are expected to have a serious or non-serious case. Dyspnea, cough, fever, and myalgia are some of the COVID-19 related symptoms, while cases of positive patients who were intubated or who were admitted to the Intensive Care Unit (ICU) correspond to serious cases. In this work, the detection of COVID-19 is proposed through the symptoms that a patient presents, and in case of being positive for COVID-19, the level of risk in which the patient will be found is determined. Regarding this, it is proposed to use the database of the *Sistema Nacional de Vigilancia Epidemiológica* (SINAVE) for monitoring possible cases of COVID-19 in Mexico City, which contains information on the characteristics of people detected as possible positive cases of COVID-19 and its severity, and to carry out both the detection of positive cases and severe cases, it is proposed to use artificial multilayer perceptron neural networks. Experiments were carried out varying different parameters of the artificial neural network, the best result obtained an accuracy of 87.68% using an artificial neural network with 3 hidden layers.

Keywords: pattern recognition, artificial neural-networks, COVID-19

I. Introduction

At the end of 2019 a new kind of pneumonia of unknown origin was discovered in the city of Wuhan, China caused by a new coronavirus type (SARS CoV-2), afterwards, the UN named this biological agent as COVID-19 [1, 2]. By December 2019 and February 2020, a total of 20,630 positive cases were notified in 244 different countries [3]. Around 83M new cases of COVID-19 were registered in 2020 and 198M of contagions in 2021 according to data from the WHO, meanwhile, around November 2022 a total of 634M of cases were confirmed [4] and up to February 2023, 755M of cases were confirmed with a total of 6.8M deceased [5]. Although there have been different variants (and subvariants) such as Alpha (B1.1.7), beta (B.1.351), gamma (P.1), delta (B.1.617.2) and omicron (B.1.1.529) among others [6], some of the symptoms presented between different variants are similar, some of them more frequent such as headache, sore throat, fever, congestion or runny nose and fatigue, in addition there are other symptoms that deserve more care in the patient such as chest pain, dyspnea or low oxygenation [7, 8].

Although the PCR test is a quick and precise way to diagnose COVID-19, because of this, a couple of works that make use of computational tools that allow the quick detection of the COVID-19 have been developed. Inside the field of the automated learning there are works that permit the COVID-19 detection via x-ray image analysis of thorax [9, 10, 11] or x-ray lung imagery [12, 13], while other works make use of voice signals [14], and there's also works that in addition to voice, cough and respiration were added [15, 16], on the other side the work pointed in. [17], exposes the importance of textual information treatment for its classification, as well as it considers x-ray image analysis, textual information is also relevant to determine the probability of presenting early signs of COVID-19, the system presented makes a text classification based on the integration of multiple information sources that can apply to COVID-19 detection based on thorax radiology. Health information systems are of the utmost importance for decision making, consequently, the work shown in [18] used COVID-19 vigilance logs found in the SINAVE and related deaths from the National e-Death Certificates Information System (SICO) to compare morbidity data, through the application of Charlson and Elixhauser comorbidity algorithms. By its own means, the works shown in [19] has the objective of quality evaluation issues and to suggest solutions from the COVID-19 dataset given by the *Ministario da Saude* of Portugal. Other papers such as [20] examine patient history data to describe hospitalization rates, ICU admission, and in-hospital mortality from COVID-19. For their part, [21] performed a multivariate logistic regression analysis to determine the effects of age, sex, previous medical condition, and symptoms on the probability of positive and hospitalization from surveillance data collected among suspected cases. of COVID-19. In addition to the positive cases of COVID-19, there are works whose purpose is to study the factors that can lead to a case of risk. In [22] they conclude that advanced age and low platelet count are associated with the severity of COVID-19, and in [23] they attribute that older people tend to seek medical care later, resulting in higher rates. discharges of severe symptoms.

The SINAVE database has follow-up information of possible COVID-19 cases in Mexico City, it also contains information on the characteristics of people detected as possible COVID-19 positive cases since January 10^{th}, 2020. The database has demographic information as well as symptoms presented by diagnosed people as positive and negative cases of COVID-19, besides, it contains relevant information on acute and non-acute cases. This paper has the objective of make use of automated learning to detect positive COVID-19 cases given the set of people’s presented symptoms and SINAVE logs, also to discriminate positive cases into acute and non-acute, to do so, multilayer perceptron based artificial neural networks were used to take on automated learning.

II. Basic concepts

II.1 Machine Learning

Supervised learning

Artificial intelligence (AI) represents a breakthrough in the area of intelligent systems, computing and data processing system, whose purpose is used to improve different types of services. A subfield of AI corresponds to automatic learning whose purpose is to simulate machine learning processes with the purpose of making predictions or classifications from a data set. Within machine learning, supervised learning is found, and it is responsible for creating automated learning models from objects that are known in advance to what type of class or label they correspond to. K-NN, SVM, Random Forest and artificial neural networks are some of the algorithms used in supervised learning [24-26].

II. 2 Artificial Neural Networks

An artificial neural network (ANN) is a computational model based on the behavior of biological neural networks. One of the tasks of ANN's is automated learning. To enable ANN learning a training dataset is required, and to acquire precision data a test set is required. There are different types of ANN's like: single layer, simple perceptron, multilayer perceptron (MLP), convolutional (CNN), recurrent (RNN), feedback based or radial based (RBF) among others.

MLP is an artificial neural network composed by an input layer, output layer and N hidden layers. An activation function is responsible for information transmission to the next layer of interconnected neurons until the reach of the output layer. Table 1 shows activation functions and the respective formulas.

Activation Function	equation
relu	$\max(0, x)$
sigmoid	$\frac{1}{1+e^{-x}}$
softmax	$\frac{e^{x_i}}{\sum_{j=1}^{K} e^{x_j}}$, K is the number of classes
softplus	$\ln(1+e^{x})$
softsign	$\frac{x}{1+\|x\|}$
tanh	$\tanh(x)$
selu	$\begin{matrix} \lambda x \; if \; x \geq 0 \\ \gamma\alpha(e^{x}-1) if \; x < 0 \end{matrix}, \alpha = 1.67, \lambda = 1.05$
elu	$\begin{matrix} x \; if \; x > 0 \\ \alpha(e^{x}-1) \; if \; \leq 0 \end{matrix}, \alpha = 0.3$

Table 1. Activation functions

The optimization function has the objective of parameter value optimization whose objective is to reduce error generated by the ANN; this process is done by backpropagation method. *Adam, Sgd, RMSprop, Adadelta, Adagrad, Adamax, Nadam and Ftrl* are some of the backpropagation functions used.

III. Materials and methods

This section shows the methodology that permits the detection of a symptomatic COVID-19 person given an MLP ANN. For such purposes, the SINAVE database was used in Mexico City.

The SINAVE database has a data set of 89 characteristics or registered fields, some of these correspond to patients specific information like gender, age, nationality, job, for woman, if pregnancy present and how many months; some other fields have information like area of residence; also, there are fields that point out to symptoms presented by the patient in which it was concluded as COVID-19 positive or negative, symptoms such as diarrhea, headache, myalgia, vomit, dyspnea among others; other information contained in the data set corresponds to patient conditions such as obesity, smoking and heart disease, among others. There's also relevant information associated with severe or non-severe cases of COVID-19 such as the *evoluci* field which classifies patients according to the severity presented, or the intubated or *icu* field which are directly associated with severe cases. The first step consists of eliminating those fields that are not necessary, such as the field *origen*, which consists of a record to find out if the patient was diagnosed within the Influenza Monitoring Health Units (USMI) or outside it; the *sector* field, which identifies the USMI in which the patient was diagnosed belongs to a public or private health institution; the *naciona* field, which indicates the nationality of the patient; *labora*, which indicates the clinic where the test was taken from the patient. These are some fields that were removed, finally 30 fields were removed. The second step consists of converting the information contained that is stored in the data set in the form of text to integer values that can be entered into an artificial neural network. Fields such as fever, cough, dyspnea, irritability, diarrhea, chills, headache, myalgia, and vomiting, among others, were assigned the following values: 1.- Ignored, 2.- Not present, and 3.- present. There is a field called *antivira* that indicates if the patient received any antiviral and what it was, in this case, each antiviral in the data set was assigned a specific value, remaining as: 0.- Not specified, 1.- Acyclovir, 2.- Amantadine, 3.- Ritonavir, 4.- Kaletra, 5.- Lopinavir, 6.- Oseltamivir, 7.- Rimantadine, and 8.- Zanamivir. The fields *resdefin* and *evoluci* that refer to the definitive result of the laboratory sample and the evolution of the patient at the cut-off date of the database, these contain values that are irrelevant for this work and that were not considered, only, they were considers the information from the *resdefin* field if the patient was diagnosed as a negative case or as a positive case, with values 0 and 1 respectively; and regarding the evolution field, only non-serious and severe cases were considered, with values 0 and 1 respectively, in addition, the information from the *intubado* and *icu* fields that are directly associated with severe cases of COVID-19 was considered. Finally, there are a total of 50 fields to consider, of which 46 are fields that correspond to input data to feed the ANN and 4 to output fields that correspond to positive cases of COVID-19, negative cases of COVID-19, and if it is a positive case, if it was registered as a serious or non-serious case. The parameters of the MLP model used are shown in the experimentation and results section, since the values were modified until the best results were obtained.

IV. Experimentation and results

Once obtained the data, next step is to feed the ANN, for such purposes, an MLP type ANN was chosen. For the experimental part, ANN parameters were established, such as the number of hidden layers and number of neurons per layer, the activation function per layer, the loss function, the optimization function, the evaluation metric and the training times.

Since the problem of this work consists of a classification problem, a probabilistic loss function of Binary Crossentropy type was used. While a binary precision metric was used as an evaluation metric because the outputs presented by the ANN are binary values. The first experiments were carried out with the following remaining parameters:

- 46 neurons on the input layer (corresponding to input fields), no intermediate layers and 4 neurons on the output layer.
- An activation function *sigmoid* on the output layer.
- *Adam* optimization function.
- 30 training epochs

First experiments consisted of determining the adequate percentage to be considered by the training set and the test set. For such purposes 13 experiments were done. The abscissa axis of the graph of figure 1 shows the percentage of the considered training set and the ordinate axis shows the precision that the model presented with the considered parameters. From where, it is observed that with a training set of 80% and 20% for the test set, a global maximum of 86.78% of precision is obtained with respect to the other values.

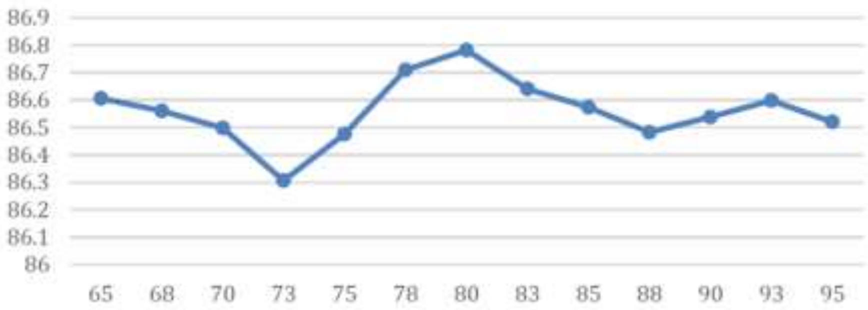

Figure 1. Percentage of the training set and MLP model precision.

The second part of the experiments consisted of determining the number of hidden layers and the number of neurons that the model must have per hidden layer. For this, first experiments were carried out where hidden layers were not considered, later a hidden layer was considered in which the number of neurons was modified. Table 2 shows the comparison of the precision that the model yields when hidden layers are not considered, and when a hidden layer with different numbers of neurons is considered.

Hidden layers	Neurons per layer	Precision (%)
0	46:4	86.78
1	46:10:4	86.87
1	46:20:4	87.08
1	46:30:4	87.04
1	46:40:4	86.86
1	46:50:4	86.98
1	46:60:4	87.26
1	46:70:4	87.40
1	46:80:4	87.50
1	46:90:4	87.37
1	46:100:4	87.35

Table 2. ANN with 0 and 1 hidden layers.

It is observed in Table 2, that a major precision is obtained when a hidden layer with 80 neurons is considered, thus, to have a more exact value, a hidden layer was considered between the range from 75 to 80 neurons, so the values on Figure 2 are obtained. A precision up to 87.51% is obtained with 79 neurons on the hidden layer.

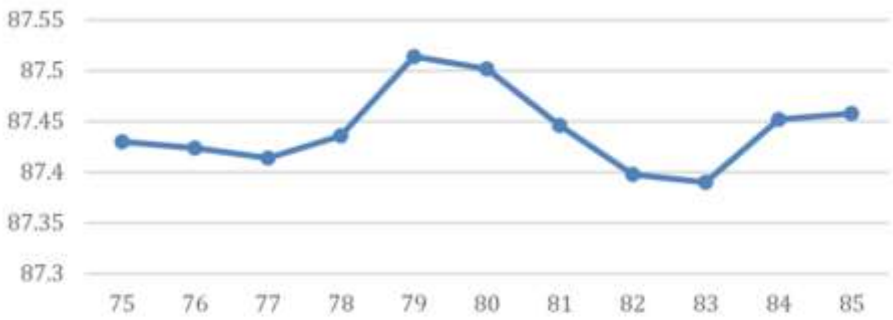

Figure 2. Number of neurons on the first hidden layer and its precision.

Once obtained the precision with a single layer, the ANN architecture was extended to 2 layers, for such purposes a first layer with 79 neurons was purposed. Table 3 shows the results obtained when 2 hidden layers are considered, first of them with 79 neurons and second layer with different amounts of neurons. In Table 3 is shown what the maximum precision is obtained when the second hidden layer is composed of 10 neurons, nonetheless, to obtain a major precision in respect to the number of neurons the second layer should have, experiments within the range from 15 to 30 neurons on the second layer were made. Figure 3 shows the results obtained, where it was obtained that the second layer with 27 neurons has a precision of 87.64%, the best result obtained.

Hidden layers	Neurons per layer	Precision (%)
2	46:79:10:4	87.27
2	46:79:20:4	87.60
2	46:79:30:4	87.54
2	46:79:40:4	87.50
2	46:79:50:4	87.42
2	46:79:60:4	87.46
2	46:79:70:4	87.51
2	46:79:80:4	87.46
2	46:79:90:4	87.43
2	46:79:100:4	87.50

Table 3. ANN with 2 hidden layers.

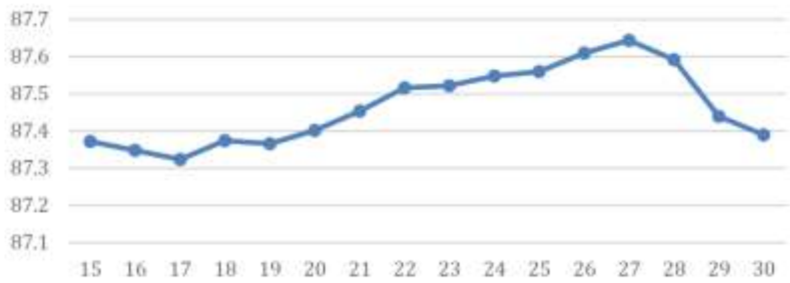

Figure 3. Number of neurons in the second layer and its precision.

Once obtained the neural network configuration with two hidden layers, first one with 79 neurons and second one with 27 neurons, it was considered the aggregation of a third hidden layer. Figure 4 shows results obtained for different numbers of neurons on the third hidden layer, from which the major precision was obtained with 30 neurons.

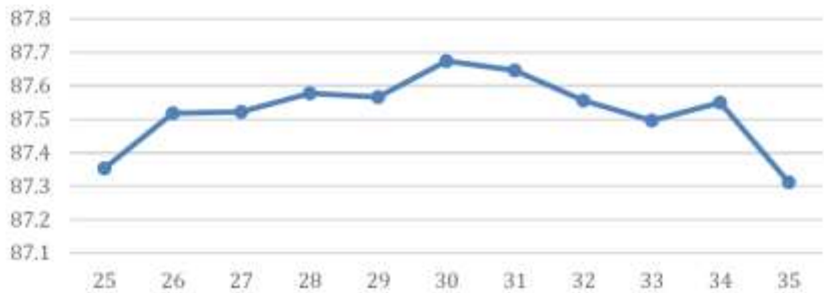

Figure 4. Number of neurons on the third hidden layer and its precision.

It was determined to use only 3 hidden layers because when the number of hidden layers was augmented, precision wasn't significatively. Finally, the ANN used makes use of an input layer of 46 neurons, an output layer of 54 neurons and three hidden layers, first on with 79 neurons, second one with 27 neurons, and third on with 30 neurons.

To select the model's adequate activation function, experiments were made layer behind layer, starting on the first hidden layer till the last one. Figure 5 shows the results obtained from the model when distinct activation functions were used on the three hidden layers. It is observed that the best results are obtained when on the first hidden layer the *softsign* activation function is used, on the second layer, *sigmoid* on the third one *softsign* and on the output layer, *sigmoid*.

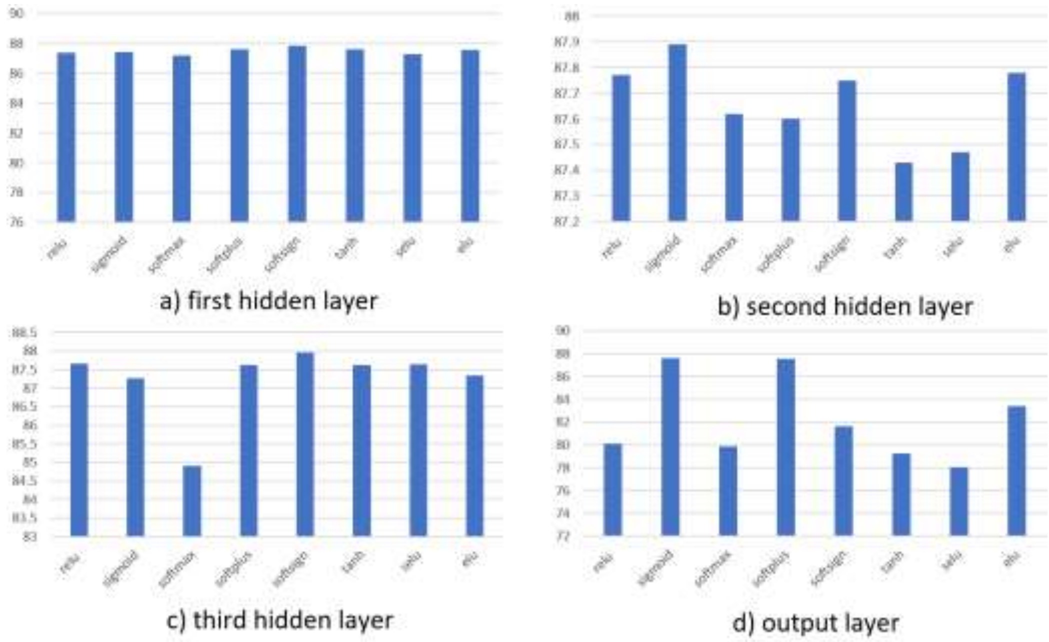

Figure 5. Distinct activation functions application on the hidden layers and the output layer.

For the election of the optimization function experiments took place considering the optimization functions such as *Sgd, RMSprop, Adam, Adadelta, Adagrad, Adamax, Nadam* and *Ftrl*. Figure 6 shows the results obtained from the application each one of the optimization functions to the ANN model, in which it was obtained that the Adam function gives the best results using 15 training epochs.

According to the obtained experiments, the MLP model that gives the best results has the following parameters:

- 80% of the logs correspond to the training set and 20% to the testing set.
- It is composed of 3 hidden layers with 79, 27 and 30 neurons respectively.
- First hidden layer makes use of the *softsign* function, second hidden layer uses *sigmoid*, third hidden layer, *softsign* and output layer *sigmoid.*

- The model makes an *Adam* optimization function.
- 15 training epochs were used.

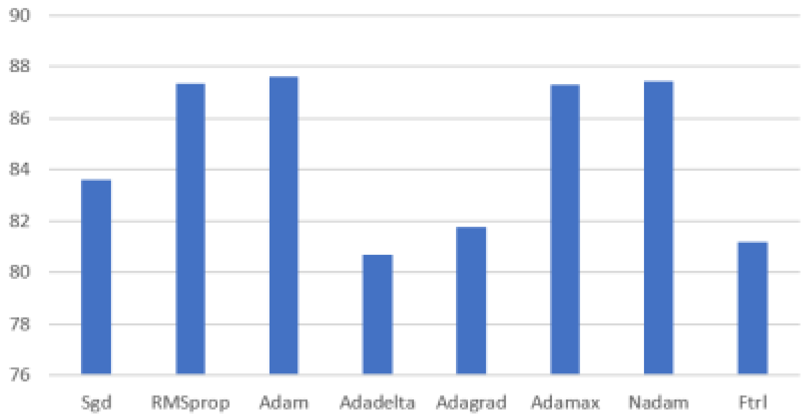

Figure 6. Application of distinct optimization functions to the ANN.

With these parameters, the model concluded with an 87.68% precision. Figure 7 shows the ANN architecture with the proposed parameters.

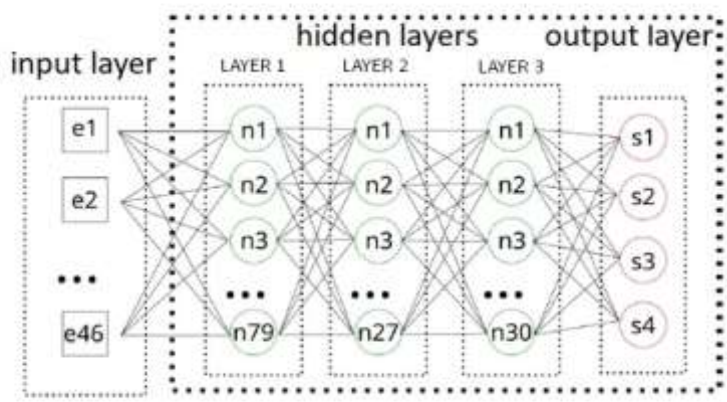

Figure 7. ANN architecture.

V. Conclusions

In this work, a methodology was shown that allows the detection of COVID-19 in symptomatic people and its severity using multilayer perceptron artificial neural networks. To carry out the work, the SINAVE database was used to monitor possible cases of COVID-19 in Mexico City, which contains information on the characteristics of the people detected as possible positive cases of COVID-19 and their severity. Initially, fields from the data set that contained unnecessary information were eliminated, leaving 46 fields at the end, which are the ones that fed the artificial neural network. The artificial neural network was built with an input layer, an output layer, and three hidden layers. The input layer has 46 neurons, the first hidden layer has 79 neurons, the second hidden layer 27 neurons, the third hidden layer 30 neurons, and the output layer 4 neurons whose values correspond to positive, negative, serious, and non-serious cases. The parameters of the artificial neural network with which the best results were obtained include applying a *softsign* activation function to the first and third hidden layers, and a *sigmoid* activation function to the second hidden layer and the output layer, in addition to using a *Adam* type optimization function and 15 training epochs. The precision value obtained with these parameters was 87.68%.

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