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Analysis Impact of Coronavirus in the Kingdom of Saudi Arabia by Using the Artificial Neural Network

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Abstract. We suggested an artificial neural network (ANN) in a medical model for covid-19 patients in this study, and we interfaced their medical data Symptoms that accompany the disease before and after the medical examination. The findings of the questionnaire were displayed. Using a specific neural network for analysis It's possible that the results will be extremely precise. The results revealed that applying style (ANN) to estimation yielded high-precision results. The symptoms of the new sickness were also investigated.

Keywords. COVID-19, artificial neural networks, Radial basis function networks, Statistical analysis

1. Introduction:

With a greater understanding of the harm caused by infectious diseases, such as COVID-19 in [1], the demand for AI in human stress management is expanding.

In domains including shape recognition and variable prediction, as well as a variety of civic and military applications, neural systems have produced excellent results in [1]. After the identification of a novel mutant "Omicron," the neural network method was utilized to characterize the signs connected to the developing corona virus in [2]. In the study, 300 people infected with Covid-19 disease completed a questionnaire, and the patient data was then interfaced in a neural network method as a mathematical analytical study of artificial neural network algorithms in the suitability of a model for medical diagnosis and the association of factors associated with medical diseases (Covid 19) in [3].

The goal of the research is to use artificial neural networks to handle the problem of linear and non-linear data using the spss program, as well as to determine the accuracy of analyzing data with multiple interpretations (ordinal - qualitative - quantitative). Artificial neural networks are an example of a wide range of intelligent systems technologies with applications in a variety of modern scientific fields that necessitate understanding of the type of model by which data (input) is converted into output (target), which traditional mathematical and statistical methods cannot. Many of the network applications investigated did not take into account the appropriate model that corresponds to the input data with a different data type, resulting in a model selection perturbation to a negative return, which might include doing needless tasks. Artificial Neural Networks (ANNs) perform better than other methods for analyzing viral data, Algorithms for machine learning are included [6]. There is significant evidence that ANNs are more effective than traditional methods at evaluating accumulated data. The findings were confirmed in [7].

Artificial neural networks have the advantage of linking factors between coronavirus symptoms before and after vaccination, as well as the ability to uncover hidden associations between viral components by detecting routes beneath a complex set of data. As a result, in [8], the artificial neural network can study the complicated relationships between coronavirus strength and frequency and vaccination milk. The use of nonlinearity in coronavirus research brings up new avenues for investigation. In AVM, nonlinearity involves a reevaluation of how the new environment is experienced and how the psychological adapting process changes in terms of theory construction [9].The use of artificial neural networks allows us to investigate a variety of Corona virus health parameters, including patient-specific factors (age, occupation, weight, and gender), chronic disorders, and status before and after vaccination [10]. An artificial neural network (ANN) has been proposed in various previous studies. A model for estimating and forecasting the number of confirmed and recovered COVID-19 cases in the days ahead, up to September 17, 2020. The suggested model is based on previously published Saudi Arabian data (training data) in [10]. Artificial neural networks (ANNs) are a form of computer network that solves issues using artificial intelligence. There isn't much research on the symptoms of Corona virus infection as a result of infection, particularly before and after the vaccine, and it's worth noting that many studies use neural networks to analyze it. As a result, research is extremely important. The majority of statistical study on the Corona virus, on the other hand, focuses on the number of people who have been infected.

2. Study Methodology

The multilayer perceptron (MLP) neural network capabilities of IBM SPSS 27v were used. This function is used to do calculations that reduce the probability of default. The neural network employed in this study included three layers: an input layer, a hidden layer to characterize the hidden neurons [13–15], and an output layer with a category node to calculate the weighted sum from the hidden layer outputs [15,16] and compute the index class for the input pattern. In one and two hidden layers, the model was constructed through trial and error with various node combinations (s). As an experiment, several partition rates were utilized.

2.1. The ANN Methodology

Artificial neural networks (ANNs) are widely utilized computation methodologies for assisting in the resolution of a variety of issues by simplification of animal brain activities [16]. Perceptron-type neural networks cover artificial neurons (PTNNs).

These nodes are the information processing units in PTNNs. Synaptic weights connect artificial neurons, which are similarly structured in layers (connections). The neurons can screen and transfer data in an on-demand administered approach to construct an analytical model that can classify data stored in memory based on this information processing style.

Three-layer network models with interconnected artificial neurons are commonly used to generate ANNs (the input layer, the hidden layer, and the output layer). Between the neurons of the input and output layers, researchers can establish one or more hidden layers. Furthermore, while no links exist between neurons in the same layer, each neuron in the layer below can be linked to a neuron in the same layer (Figure 1).

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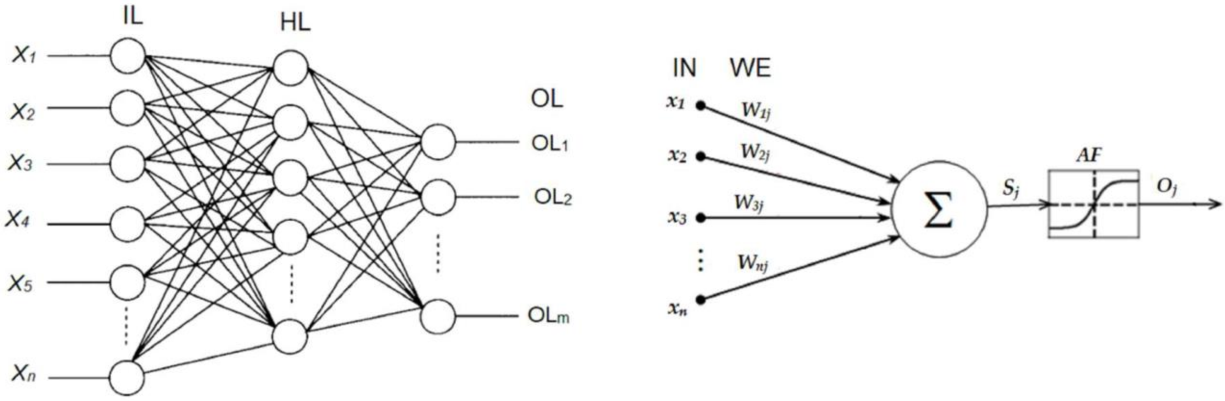

(a) (b)

IN—inputs, WE—weights, AF—activation function, Sj—sum of the weighted input, and Oj—output activation function; IN—inputs, WE—weights, AF—activation function, Sj—sum of the weighted input, and Oj—output activation function; IN—inputs, WE—weights, AF—activation function, Sj—sum of the weighted input, and Oj—output (b) IN stands for inputs, WE stands for weights, AF stands for activation function, Sj stands for sum of the weighted input, and Oj stands for output activation function. The data processing is completed by the hidden layer after the input layer obtains statistics about variables from the created dataset.

The output layer is used to forecast continuous measures and is designed to provide categorical class labels (see Figure 1a). To the inner of the hidden node, the input layer values are multiplied by the weights, which are a set of predetermined values. After that, all of the measurements are combined to generate a single value that is utilized as an argument in an ANN's activation function, which is a nonlinear mathematical function (AF). The nonlinear AF produces a number between 0 and 1. The net sum of the weighted input values entering node j and the output activation function (see Figure 1b) that translates the neuron's weighted input to its output activation (the most usually used is the sigmoid function) can be represented using the following equations:

$$\mathrm{Sj} = (x + a)^n = \sum_{i=1}^{n} \mathrm{xiwij} \qquad (1)$$

$$\mathrm{Oj} = \frac{1}{1+e^{Sj}} \qquad (2)$$

The neurons of ANNs go through two stages of processing: training and usage. Authentic inputs and outputs are used as examples throughout the training step to train the system to predict outputs. This controlled learning starts with random weights and corrects them to be applied to the situation at hand using gradient origin inspection procedures like back-propagation. To regulate learning, the error function uses the variance amontotarget output measures and gotten measures [17]. Furthermore, the error function is associated with the weights, which must be adjusted in order to reduce the error. To provide an explanation of a specific training dataset { $(f(x) = \{ (x_1, t_1), (x_2, t_2), \ldots, (x_k, t_k)\}$ The error for each output neuron can be determined using Equation (3), which has K desigated pairs of n inputs and m dimensional routes, which can be characterized by n inputs and m outputs.

$$E_J = \frac{1}{2}(o_j - t_j)^2 \qquad (3)$$

Equation (4) can be used to show how to minimize the network's error function:

$$E_J = \frac{1}{2}\sum_{j=1}^{k}(o_j - t_j)^2 \qquad (4)$$

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When input design xi from the training dataset travels through the network, Oj is the output yield, and tj is the goal measure [18]. Each weight is changed to its previous value throughout the training stage by accumulating quantity:

$$\Delta\omega_{ij} = -\gamma \frac{\sigma \mathrm{E}}{\sigma\omega_{ij}} \qquad (5)$$

where constant is used to calculate the learning rank. According to the rule, the higher the learning rank, the faster the convergence. However, looking for high validation measures of data training is not a good idea because this search path may wrap around the optimal explanation, making convergence unattainable. After generating a dataset with credible weights, the neural network model can automatically forecast the related outputs using an alternative set of unidentified output metrics.

2.2. Multilayer Perceptron Methodology

The above-mentioned perceptron-based paradigm has some limitations; it is typically only effective for linearly identifiable data. The perceptron-based model is expanded to a more multidimensional design in the case of a non-linear dataset, especially known as multilayer perceptron (MLP) [18–21]. MLP is also known as a neural network with interconnected neuron layers, with the output of each layer's neuron serving as an input solely to neurons in the upper layer (see Figure 1). The results will be significantly better if non-linear activation functions, such as the sigmoid function, are employed for those neurons (see Figure 1b).

$$sigm(z) = \frac{1}{1+e^{-z}} \qquad (6)$$

As a result, the MLP neural network is capable of encapsulating large non-linearity in the dataset, demonstrating that by using complthe-enough MLPs, any continuous function can be approximated at the random small error. The ink weight from the i-th neuron in the -th layer to the j-h neuron in the (+1) -th layer, or (+1) j, can be used to validate the i-th neuron in the -th layer, which is defined as:

$$y_{\iota i} = f_{\iota i}(z_{\iota i}); z_{\iota i} = \sum_{j=1}^{i} \omega(\iota-1)_{j,}\, \iota_i \gamma(\iota-1)_j + b_{\iota i,} \qquad (7)$$

Where $y_{\iota i}, f_{\iota i}$ and $b_{\iota i,}$ are the output, activation function, and bias, respectively; and n_ι is the number of neurons for the ι -th layer. Additionally, that was symbolized as $y_{oi} \equiv xi$. For simplicity, a neuron is activated by the sum of weighted outputs of the neurons in the lower layer. An MLP network training technique's goal is to minimize an objective function in terms of its criteria (i.e., weights and biases) that is related to the job that the MLP is used for. The following target function could be used for binary classification.

$$\mathrm{E}(\theta) = \frac{1}{n} \sum_{(x,y)\epsilon D} (y-\hat{y})^2 \qquad (8)$$

where D is a set of training data, $\hat{y}$ can be presented as the MLP output of the prearranged input x, and θ is its dataset of weights and biases. In case of a need to reduce the objective function $\mathrm{E}(\theta)$,The gradient technique, which asserts that the total of a parameter's updte is negatively proportional to the gradient at its current value, can be utilized. The center point of the gradient

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descent method is used to compute the gradient $\frac{\sigma E}{\sigma w}$ for all $w \in \theta$, ich is easily done using the chain rule:

$$\frac{\sigma E}{\sigma Z_{LI}} = \frac{\sigma E}{\sigma y_{LI}} \frac{\sigma y_{Li}}{\sigma z_{li}} \quad (9)$$

$$\frac{\sigma E}{\sigma Z_{Li}} = \sum_j \frac{\sigma E}{\sigma Z_{(I+1)_J}} \frac{\sigma z_{(I+1)_J}}{\sigma z_{Ii}} = \sum_j \frac{\sigma E}{\sigma z_{(I+1)_J}} w_{Ii}, (I+1)_j \frac{\sigma y_{Ii}}{\sigma z_{Ii}}; \quad (10)$$

$$\frac{\sigma E}{\sigma w_{Ii,(I+1)_J}} = \frac{\sigma E}{\sigma z_{(I+1)_J}} \frac{\sigma z_{(I+1)_J}}{\sigma w_{Ii,(I+1)_j}} = \frac{\sigma E}{\sigma z_{(I+1)_j}} Y_{Ii} \ . \quad (11)$$

The back-propagation algorithm is based on this principle (BPA). The BPA adjusts ANN weights to reduce the mean squared error between the network's expected and actual outputs. BPA employs controlled learning, in which the neural network is trained on a dataset that contains both known inputs and desired outputs [23]. The network weights are identified after the training process and then utilized to compute the output measures for the original input samples. The feedforward algorithm is the way of calculation that permitted us to go too fast.
An MLP to complete the prediction (Figure 1a). According to the algorithm, the outputs of the neurons in the main layer are used to compute x first, and then the outputs of the neurons in the secondary layer**.**

2.3 The Number of the Necessary Hidden Units

In order to achieve a specific approximation order, the essential number of hidden units (NHUs) in an MLP must be computed. The NHUs also influence the amount of independent values that can be altered by modifying the network parameters, as well as the achievement of the specified approximation instruction for the randomly adequate smooth function. Furthermore, calculating a number of MLP parameters is not simple. Furthermore, the network parameters' specified NHUs are not all the same. This issue can be expressed in a variety of ways if the hidden units are spread in distinct hidden levels. Meanwhile, the goal is to locate the necessary NHUs, and it's also critical to specify the maximum number of parameters when the number of hidden units is known [24]. In a multilayer perceptron neural network with one hidden layer, where $n_0 \in \mathbb{N}$ inputs and the smooth activation function can only implement an approximation order $N_0 \in \mathbb{N}$ for all functions $f \in C^N(K \to \mathbb{R})$, if at least n hidden units are used, the following equation can be obtained:

$$\frac{\binom{N+n_0}{n_0}}{n_0+2}. \quad (12)$$

According to this fundamental result, there should be no limit on the number of concealed layers. It has been discovered that there is no need for more than two hidden levels. In most cases, one hidden layer suffices, but in some cases, to achieve the needed number of network constraints, the required hidden units must be spread across two hidden layers. The resulting Equation (13) can be used to define this:

$$\left(the \ {N+n_0 \atop n_0}\right) \leq (n_0+2)(n_0) + 1 + 2\sqrt{n_0} \quad (13)$$

where n hidden units (Equation (14) are critical for all functions to achieve complete approximation order N ,$f \in C^N(K \to \mathbb{R})$:

$$n \geq \frac{\binom{N+n_0}{n_0}}{(n_0+2)}. \quad (14)$$

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Otherwise, Equation (15) can be used to compute the hidden units required to obtain a specific approximation order:

$$n \geq 2\sqrt{\binom{N+n_0}{n_0}} + 2(n_0+1) - n_0 - 3 \qquad (15)$$

The required number of parameters can be realized by a multilayer perceptron neural network with one hidden layer, however if two hidden layers are employed, Equations (16) and (17) can be used to find the required number of parameters for MLP neural networks:

$$n_1 = \left\lceil \frac{n+n_0-1}{2} \right\rceil \qquad (16)$$

$$n_2 = n - n_1 = \left\lfloor \frac{n+n_0-1}{2} \right\rfloor \qquad (17)$$

The presented equations (Equations (12)– (17) can be used to determine the appropriate hidden unit quantity and its variation to one or two hidden layers in [24] if the number of inputs is known.

3. Description of the data

3.1 Statement of morality

Dr. Esraa Hassan, a lecturer at the Corona Vaccine Center in Najran, Kingdom of Saudi Arabia, accepted the questionnaire. Najran University's **Nahla Kamaluddin** is a Saudi Arabian academic.

3.2 Data and sample collecting

In December 2021, a random sample of 300 people in the Kingdom of Saudi Arabia was taken. The survey was completed in both Arabic and English.

Structure:

For analysis, use the spss software. For symptoms that could indicate COVID-19, data was collected using a questionnaire. The situation before and after the disease, as well as the types of data collected, were all different. The variables that show that it has a significant impact on the response variable are as follows: The initial stage in the study is to figure out what the neural network's inputs are. The following were the variables:

Table 1 shows the variables that were used in the research.

Code of a Variable	Measurement Description		
dependent variable	How many times have you contracted covid-19	Once Twice Three times	
Factor	Age	17-12 18-30 31-50 51-60 61+	
	Gender	1. Male 2. female	
	Weight	1. Very Thin 2. Thin	

		3. Normal Weight 4. A little overweight 5. A lot overweight 6. Excessive obesity	
	Job	1. Student 2. Health sector employee 3. Government employee or private sector 4. Retired 5. I don't work	
Covariates	Chronic Diseases	1. No chronic diseases 2. diabetes or hypertension 3. cardiac problems 4. liver cirrhosis 5. Renal failure 6. Cancer 7. autoimmune diseases 8. bronchial asthma or chest allergies	
	Have you taken the covid-19 vaccine	1. I did not take the vaccine 2. Single dose 3. Two doses 4. Two doses and the booster dose	
	Was the diseinfected before or after the vaccinease	1. Was the infection before or after the vaccine 2. Infection occurred after the first dose 3. Infection occurred after the second dose	
	Symptoms of covid 19 disease were	1. There are no symptoms 2. Mild symptoms 3. Moderate symptoms	

		4. Strong symptoms, but did not need to go to the hospital 5. Strong symptoms and was hospitalized	
	The difference between covid 19 injuries	1. Only got hit once 2. The first injury is more severe than the second injury 3. The second infection is more severe than the first 4. Both injuries had the same symptoms and almost the same severity	
	How long did covid 19 symptoms last?	1. No symptoms 2. From one to three days 3. From four days to a week 4. From one to two weeks 5. More than two weeks	
	Symptoms of Covid-19 disease (more than one symptom of the disease can be selected)	Fever	

Notes:
A doctor from the Corona Vaccine Center and a professor from Najran University in the Kingdom of Saudi Arabia reviewed the questions.

(4.2) Case treatment outcomes
In this study, we looked at whether the MLP neural network accurately identified the main neural network, if the dependent variable was linked to independent variables and other factors, and if the application was the correlation between the number of cases of COVID-19 disease and the symptoms that accompany it. Table 1 lists the datasets that were utilized to create the

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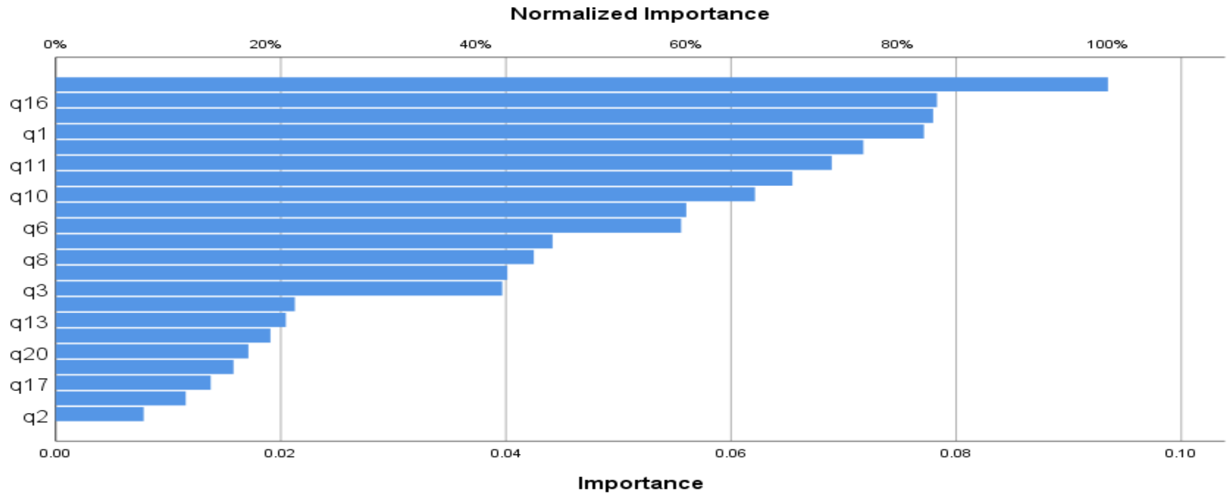
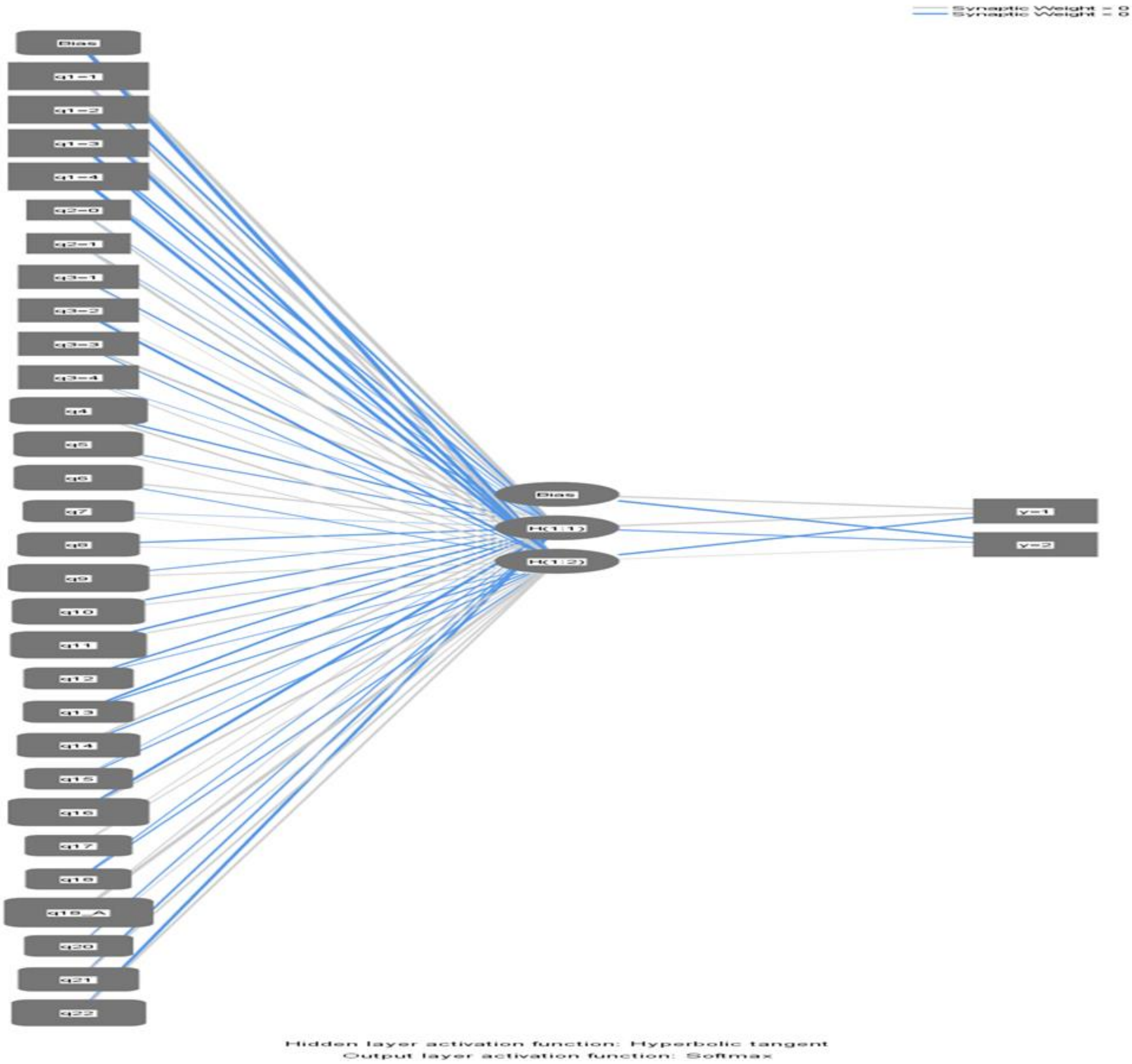
three ANN models. The amount of neurons in each layer, as well as 14 independent factors, are shown in the table: The MLP neural network was created with this in mind.
It has three nodes for computing the hidden layer and three nodes for computing the visible layer thanks to automated geometry. The dependent variable connected with perceived stress Categories is described by nodes in the output layer. For different levels, different functions were used: what does activation mean? The exaggerated

Conclusion

A backpropagation technique was used to train a multi-layer neural network to identify the number of COVID-19 infections and correlate them before and after the immunization. The maximum accuracy was achieved utilizing a single layer, according to our findings. The percentage of accurate answers is 96.2 percent.
It's a sizable proportion. The researchers suggest that future studies be conducted in other countries and that countries be compared to see how the vaccine affects the amount of COVID-19 infections using the Perception Network (PNN) learning algorithm.





A2. Illustration Multilayered perceptron with ANN2 structure for cycle time.

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