

# PREDICTION SYSTEM OF ERYTHEMAS FOR PHOTOTYPES I AND II, USING DEEP-LEARNING

## SISTEMA DE PREDICCIÓN DE ERITEMA PARA FOTOTIPO I Y II, UTILIZANDO DEEP-LEARNING

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Recibido: Abril 29 de 2015 Aceptado: Septiembre 02 de 2015

### ABSTRACT

**Background:** The sun is a natural source of electromagnetic radiation, upon which are found the ultraviolet (UV) rays, where only the types A and B are able to irradiate over the surface of the Earth in different proportions. Although the sun helps human skin in the formation of vitamin D, the mineralization of bones, and absorption of calcium and phosphorus in the organism, it can cause damage on the skin by prolonged exposure to UV radiation, generating adverse effects on human health like erythema formation, photo-toxicity, photo-allergy, idiopathic lesions, and photo-dermatitis, among others. This paper, shows the results of developing a prediction system of the exposure time of a person to UV rays coming from the sun, which can cause erythema on human skin, using the standards in UV index and the dose limits of radiation allowed for phototypes I and II, aiming to foresee the generation of these kind of lesions. This was made by the implementation of artificial intelligence algorithms like Deep Belief Networks and Backpropagation, based in the Deep Learning technique. These algorithms use as training parameters for the neural network, the meteorological data such as the sky clearness index, the radiation on the horizontal surface and average air temperature, supplied by the National Aeronautics and Space Administration (NASA). With the data, a neural network aiming to foresee the UV index for the following year of the data input was trained, in addition some mathematical regressions were applied allowing in this way, to obtain an approach to the behavior of the UV index along the day. Likewise, this information was used to estimate the maximum time of sun exposure, for the period of time contained between 6:00 a.m. and 6:00 p.m. This paper, also presents some conclusions based in the results found, which try to establish some important considerations in order to implement the neural networks.

**Keywords:** Erythema, photo-type, ultraviolet index, prediction, artificial intelligence

### RESUMEN

**Resumen:** El sol es una fuente natural de radiación electromagnética, en la cual se encuentran presentes los rayos ultravioleta (UV), de los cuales solo los tipos A y B (de Paula Corrêa, 2005) pueden irradiar sobre la superficie de la tierra en distintas proporciones. Aunque el sol le ayuda a la piel en el proceso de formación de la vitamina D, además de favorecer la mineralización de los huesos, y la absorción de calcio y fósforo en el organismo, puede ocasionar daños sobre la piel ante exposiciones prolongadas a la radiación UV, generando efectos adversos sobre la salud humana como eritemas, foto toxicidad, foto alergia, lesión-

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nes idiopáticas, foto dermatitis, entre otras. En este trabajo, se presentan los resultados del desarrollo de un sistema de predicción del tiempo de exposición de una persona, a rayos UV provenientes del sol, que pueden producir eritemas sobre la piel, utilizando la estandarización del índice ultravioleta y los límites de dosis de radiación permitidos para los fototipos cutáneos I y II, con el objetivo de prever la generación de este tipo de lesiones. Esto se realizó a través de la implementación de algoritmos de inteligencia artificial como Deep Belief Networks y Backpropagation, basados en la técnica de Deep Learning. Este algoritmo, utiliza como parámetros de entrenamiento para la red neuronal, los datos meteorológicos como el índice de cielo despejado, la radiación sobre la superficie horizontal de la tierra, y la temperatura promedio del día, provistos por National Aeronautics and Space Administration (NASA). Con estos datos se entrenó una red neuronal con el objeto de pronosticar el índice UV del año posterior a los datos de entrada, adicionalmente se aplicaron algunas regresiones matemáticas permitiendo de esta manera, obtener una aproximación al comportamiento del índice UV a lo largo del día. De igual manera, esta información se empleó para estimar los tiempos de exposición solar máximos, para el periodo de tiempo comprendido entre las 6:00 a.m. y las 6:00 p.m. En este artículo, también se presentan algunas conclusiones basadas en los resultados encontrados, las cuales tratan de establecer algunas consideraciones importantes para implementar este tipo de redes neuronales.

**Palabras clave:** Eritema, fototipo, índice ultravioleta, predicción, inteligencia artificial

## INTRODUCTION

The Sun as object of study has acquired a great importance, on account of its capability of energy transmission, through electromagnetic radiation. This radiation is classified according to wavelength, which has a tight relation, with the quantity of energy transmitted by a photon, as is exposed by Calle *et al* (2009). (2). This has contributed to create a space in the knowledge society, dedicated to study methods to obtain energy stemming from the Sun. Nevertheless, this kind of radiation is responsible of some adverse effects on human health as is presented by Allen *et al.* (2008) (3) and Goldsmith *et al.* (2008) (4).

Today there are some developments with technological character, which use the relation between the UV radiation and human health, as is the case of Amini *et al.* (2008) (5), where a wireless device for the monitoring of the UV rays is built. In addition, other researches allow the generation of maps for meteorological variables, as shown in Calle *et al* (2009). (2) and Na *et al.* (2012) (6), which are generated from irradiance data over Spain and the South Korea territory, respectively. These investigations show interest in the study of this kind of rays which are able to cause, inhibition of the immune system, visual disruptions and skin cancer (7), considered the most common into these kind (5) of problems. In response to the previous health difficulties caused by UV rays, estimated close to 5% of radiation stemming from the sun (5), different institu-

tions such as the World Health Organization, the World Meteorological Organization, among others, promote the research about phenomena related with the sun, which allow them to issue concepts as the consigned by OMS (2012) (8) related to the thematic, whose objective is to prevent unwanted effects over human health.

The consolidation of the techniques and algorithms, in the area of artificial intelligence allowed the development of systems able to predict meteorological aspects, through the implementation of neural networks as is shown by Linares *et al.* (2011) (9), for the daily generation of radiation data using variables like the clear sky index, the earth skin temperature, among others. By the other hand, Bendekhis M *et al.* (2005) (10) implement the Radial Base Function architecture, with the objective to predict solar radiation data for autonomous photovoltaic systems.

The erythemas are a kind of common lesion over the skin, generated by exposure to UV rays where its severity, change in function of the skin types of the people (3). Researches like the presented ones in Lu *et al.* (2010) (11), show the application of machine vision algorithms, with the objective detect the presence and severity of erythemas in human skin. In Ahmand *et al.* (2009) (12) is presented a method to make the valuation of the severity of the erythematous lesion, present in the psoriasis illness based in the "PASI" index, from the analysis of the color affected area with the parameters of the CieLab color space. This index is used in Hanny

*et al* (2012) (13) for the valuation of erythemas, through the implementation of Fuzzy-C means Algorithms, based in the swelling and color lesion, taking into account the skin color or phototype of the test subject.

This development aims to foresee the generation of erythematous lesions, for people classified into phototype I and II, taking into account that these skin types have a sensitive behavior in the face of sun exposure (3). This prediction is made from the yearly forecast, of the average UV index per day, from the meteorological data of previous years, available in the NASA data base (14), through the development of an application which uses an artificial intelligence structure called deep learning.

This paper, in its first section introduces the thematic of electromagnetic radiation supplied by the sun, showing a group of investigations which implement neural networks for the prediction of meteorological variables, followed by a second section where various health problems related with sun exposure, important for the development of the work are presented. Presenting as well, the developed structure and the implemented neural network architecture in the research. In the third section the final results are shown, as well as the developed application, and the final tests which allow to observe a percentage of the quantity of UV index correctly foreseen. Finally, in the fourth section the conclusions obtained during the development of the work and future perspectives are presented, which aims to give depth to the object of study.

## MATERIALS AND METHODS

### Health and UV radiation

The ultraviolet radiation is able to influence human health, by affecting the cells. The interaction with ionizing radiation can generate pathologies as photo-toxicity, photo-allergies, photo-dermatitis, among others by deficiency in the DNA (2). One of the most serious problems, generated by long periods of sun exposure is skin cancer, given by the propagation of an error into the DNA structure (15).

The exposure UV rays produced by sun, even by artificial sources can cause a severe inflammatory response, characterized by having a transitory delayed and temporal manifestation in the skin, which is known as solar erythema (3). This kind of problem depends strictly, of the quantity of UV radiation supplied during an exposure time and the vulnerability of each human.

Basing in the skin type and its response against to sun exposure, Thomas Fitzpatrick defines six kind of skin called phototypes (16). This classification allows establish the vulnerability for each kind of person, in such a way that the phototype I needs the shortest time of exposure to generate an erythema.

In function of the skin phototypes, the concept of minimal erythematous dose was established, which expresses the quantity of absorption of UV radiation able to generate a problem after 24 hours of sun exposure (3), as well as the value for phototypes I and II being considered in an interval from 200 to 250 J/m<sup>2</sup> (2, 17). From this concept and the UV index, it establishes the relation shown in the equation 1 (17), which express the maximum time sun exposure in minutes.

$$T = \frac{DME \frac{mJ}{cm^2}}{Indice UV \times 0.15 \left[ \frac{mJ}{cm^2} \right]} \quad \text{Equation 1.}$$

The UV index is calculated using equation 2 (5, 19), which is defined by the erythematous irradiance, dependent of the solar irradiance at wavelength  $\lambda$  (2), which in this case was assumed as 350nm for UV rays type A, and 300nm for type B. Taking into account that the UVA rays have a wavelength from 400nm to 328nm, and the UVB from 328nm to 298nm.

$$I_{uv} = 40 \frac{[m^2]}{[W][nm]} \int_{250nm}^{400nm} E_{\lambda} S_{er}(\lambda)(d\lambda) \quad \text{Equation 2.}$$

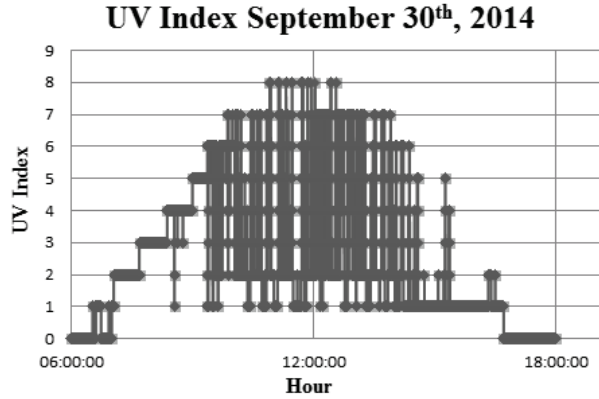
Using equations 3, 4 and 5 the coefficient  $S_{er}$  called erythema action spectrum can be calculated, which describes the spectral weighting function for erythema (18). This parameter depends of the wavelength of the UV rays, in nanometers (nm).

$$S_{er}(\lambda) = 1 \quad \text{for } 250 \text{ nm} \leq \lambda \leq 298 \text{ nm} \quad \text{Equation 3.}$$

$$S_{er}(\lambda) = 10^{0.094(298-\lambda)} \quad \text{for } 298 \text{ nm} < \lambda \leq 328 \text{ nm} \quad \text{Equation 4.}$$

$$S_{er}(\lambda) = 10^{0.015(140-\lambda)} \quad \text{for } 328 \text{ nm} < \lambda \leq 400 \text{ nm} \quad \text{Equation 5.}$$

In Figure 1, the behavior of the UV index for September 30<sup>th</sup> 2014 is shown, which approximates to a mathematical model called Gauss function (8), where the instant clear sky index, affects directly the measurement. This process is made by capturing the instant radiation in  $W/m^2$ , using the Delta Ohm HD2102.2 radiometer, connected to an application developed by the work group, oriented to the monitoring and storage of this information.



**Figure 1.** Ultraviolet index measurement from 6:00a.m to 6:00 p.m.

The likely behavior of UV index, with a clear sky, is defined by equation 6, where  $\mu$  and  $\sigma$  are constants proper of the Gauss function, equal to 12 and 1.5 respectively. These values were found, through the characterization of the UV index behavior, during a period of 25 days, compromised from the 5<sup>th</sup> to 30<sup>th</sup> of September 2014, as was earlier noted.

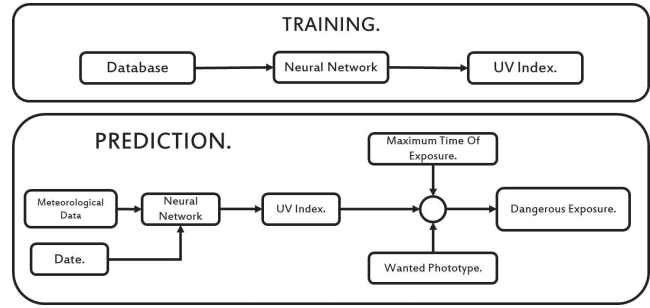
$$UVI_{(t)} = [UVI_{max}] [e^{-0.5(\frac{x-\mu}{\sigma})^2}] \quad \text{Equation 6.}$$

In addition, the data obtained during September helped finding the relation exposed in the equation 7, used to estimate the maximum value of the UV index, from the average captured during the day.

$$UVI_{max} = 1.973 * UVI_{av} + 1.645 \quad \text{Equation 7.}$$

### Development Structure

The development structure shown in Figure 2, sets out the implementation of an application based in two processes. The first one has as objective to carry out training for a neural network with a database, made from meteorological data supplied by Near Real Time Daily Global Radiation and Meteorology (14), belonging to National Aeronautics and Space Administration NASA.



**Figure 2.** Structure for the solution

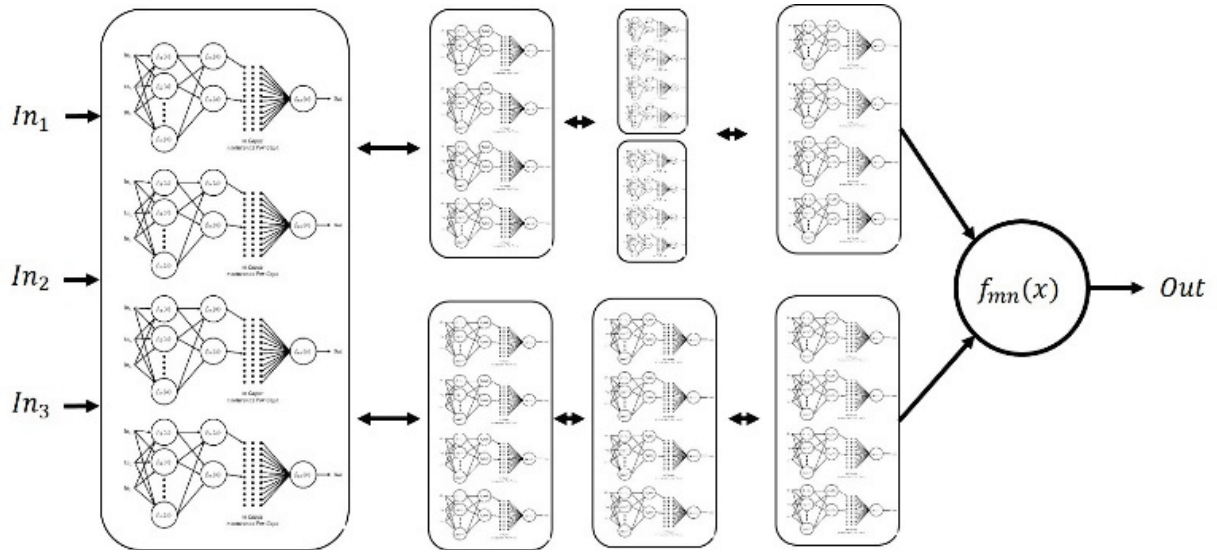
The second part of the application, aims for the prediction of the adverse effects in the skin. This process is made, from meteorological data of previous years, taking as a base the neural network previously trained. Once the artificial intelligence algorithm predicts the UV index, this application continues with a study to find minimum time of sun exposure to generate an erythema, taking as reference the features for phototypes I and II.

### C. Deep-Learning

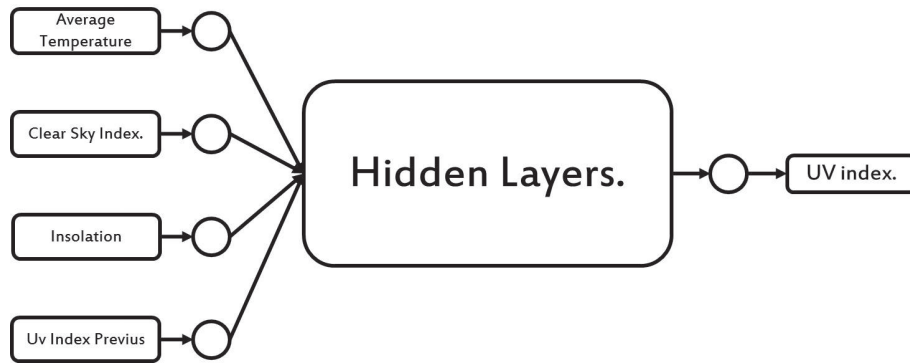
Deep learning is a type of artificial intelligence architecture, belonging to the field of machine learning. This architecture is compound by multiple levels of non-linear operations, called processing units (19). This kind of technique is characterized by the extraction and transformation of characteristics of the information.

For the training of the deep learning network, a Backpropagation algorithm is implemented using the structure shown in Figure 3, which makes the update of weights according to the average squared error, generated in every iteration (20). This network is implemented under supervised learning, where it can be found five inputs and one output.

The prediction of the generation of erythemas in humans, especially for phototypes I and II is made through the UV index. The structure used is shown in Figure 4, where the previously mentioned UV index, is predicted from meteorological data such as average air temperature at 2 meters high, the earth skin temperature, insolation, the clear sky index, the radiation on the horizontal surface, and the average UV index for the same day in the previous year. This data was collected for a latitude of 4.6831° and a longitude of -74.0427°, from the Near Real-Time Daily Global Radiation and Meteorology database (14).



**Figure 3.** Multilevel Structure

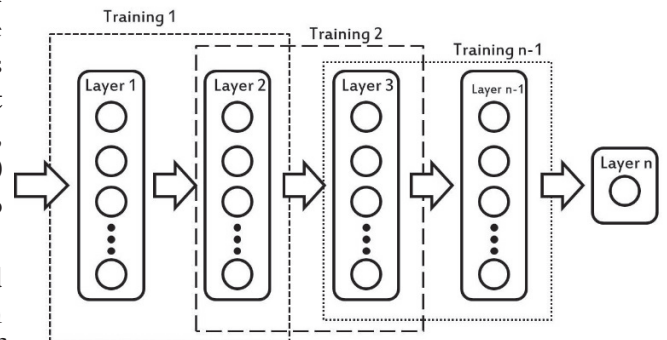


**Figure 4.** Architecture of neural network used

The Deep Learning structure, implements a larger number of hidden layers, that allow a better approach to the features formulated in (21). However, a suitable relation between the numbers of hidden layers, and the quantity of neurons within are proposed, with the objective of decreasing the time of training. The advantage of implementing this type of architectures over others, as Adaline and Madaline is the increase in precision and decrease in the time of convergence of the algorithm, for this kind of complex systems. In this way, the present paper proposes a structure for the neural network, based on 20 hidden layers each conformed of 50 neurons, and the last layer has one neuron, due to its feature of having one output.

The first training is made through the method of Deep Belief Network (DBN), which is based on probabilistic models composed by multiple levels of layers and hidden variables. In this unsupervised

learning, the training takes two layer per time, where the first one works as hidden layer, and the second one as output layer. Then, the output variables are taken as parameters for the input in the next layer, and the procedure is repeated, until arriving to the penultimate layer of the neural network (22), as shown in Figure 5.



**Figure 5.** Structure of training for deep belief network



Later, the Backpropagation method is used as an unsupervised training of the neural network. This training adjusts the values of the weights and gains, in function of the generated middle squared error (23). In this phase, the values to adjust are modified using a new group of data, in each of the iterations (20).

The Backpropagation method allows to define some values with the objective to improve the performance of the neural network increasing the velocity of training. Among these values is the learning rate, which influences directly the update of the values of the weights, and is adjusted to find the balance, between the velocity of convergence and the stability of the weight values. In addition, the concept of momentum is included, which limits the excessive oscillation of the weight values, trying to avoid great changes in these, behaving as a smooth factor to optimize the time of convergence of the algorithm (23).

## RESULTS

As a final result, an application in C# was made using Visual Studio® tool, where the interface shown in Figure 6 is generated. Whose objective is to foresee the generation of erythemas on human skin. The application has different modules of development, where the training of the neural network, the forecast of UV index for a fixed period and a simple prediction from data for a given day are made. The interface presents two graphics, in the first one the forecast of the average UV index is shown, given a certain input data. In the second graphic, the behavior of the UV index during the wanted day is presented, which is applied for computing the maximum time of sun exposure, in an interval from 6:00 to 18:00.

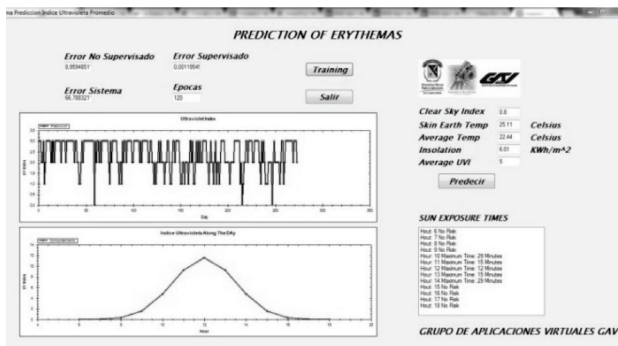


Figure 6. Interface Implemented

The simple prediction mode shown in Figure 7, allows the prediction of the time necessary to generate an erythema, from the parameters meteorological of the same day in the previous year. This prediction gives as results the average UV index foreseen for the wanted day, with which will be anticipated the hours with the highest risk for skin health. This application was configured to work in the unit system advised by the world meteorological organization (24).

Figure 7. Parameters for Prediction

Once the average UV index is obtained, through the prediction of the neural network, the maximum UV index is obtained with equation 7. Later, equation 6 is used to find the behavior of the UV index, disregarding the interferences generated by the clouds. Figure 8 shows the estimation of this behavior for the values shown in Figure 7.

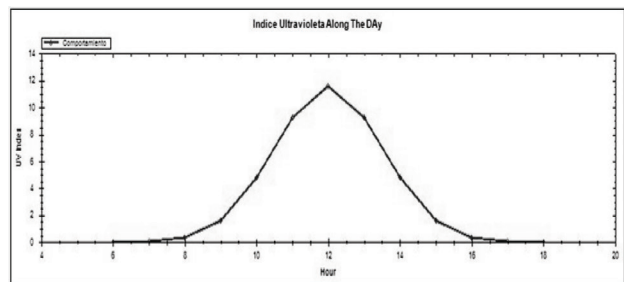


Figure 8. Prediction of the UV index behavior along the day

From the prediction of the UV index behavior shown in Figure 8, as well as the implementation of equation 1, the maximum time in minutes is found, which puts in risk the skin health of a person with a phototype I or II. In Figure 9, the time slot of risk from 10:00 a.m. to 3:00 p.m. can be seen.

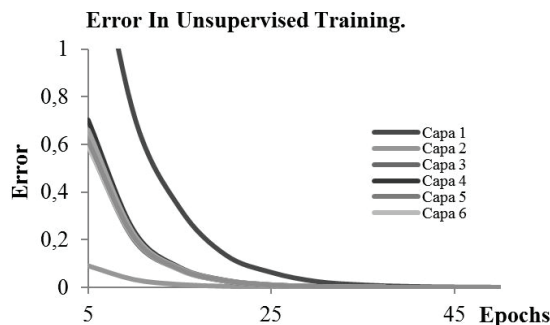
SUN EXPOSURE TIMES			
Hour: 6:00	UV Index :0	No Risk	
Hour: 7:00	UV Index :0	No Risk	
Hour: 8:00	UV Index :0	No Risk	
Hour: 9:00	UV Index :1	No Risk	
Hour: 10:00	UV Index :4	Maximum Time: 35 Minutes	
Hour: 11:00	UV Index :8	Maximum Time: 18 Minutes	
Hour: 12:00	UV Index :10	Maximum Time: 15 Minutes	
Hour: 13:00	UV Index :8	Maximum Time: 18 Minutes	
Hour: 14:00	UV Index :4	Maximum Time: 35 Minutes	
Hour: 15:00	UV Index :1	No Risk	
Hour: 16:00	UV Index :0	No Risk	
Hour: 17:00	UV Index :0	No Risk	
Hour: 18:00	UV Index :0	No Risk	

**Figure 9.** Prediction Time Needed To Build A Minimum Erythema

## DISCUSSION

Thanks to the given technique, results that contribute to preserve the health of people by giving the proper amount of time of solar exposure to avoid erythema could be performed. Exposing an innovative way of implementing artificial intelligence in the field of human health, as it allows the user to know the maximum time of exposure at a given hour using an easy to read interface.

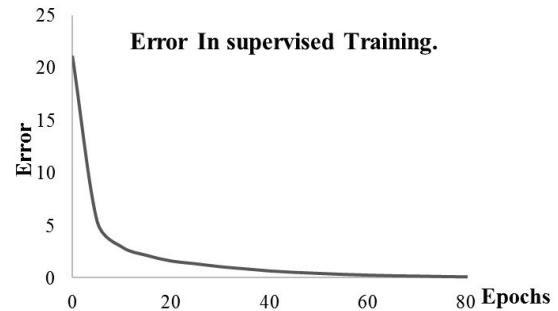
The application consists of a module for the training of a neural network divided in two stages. The first one consists of a Deep Belief Network algorithm, as earlier noted in II.C. In this training, the first and the second hidden layer begin with the maximum and minimum errors respectively, while the remaining layers, that means, from the third until the last layer, have similar patterns. However, as is noted in Figure 10, all the hidden layers without exception coincide in nearly 50 epochs.



**Figure 10.** Error In the Layers of the Neural Networks

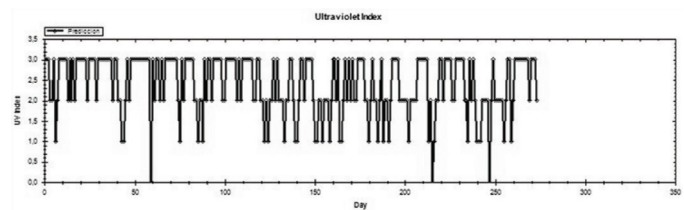
In the second phase a supervised training is made, taking as base the backpropagation method. This procedure uses as input information, the meteorological data for each day of the year, which

are compared with the output information, corresponding to UV INDEX for the same day in the next year. In Figure 11, the behavior of the error along each epoch of the training is shown. It can be seen that this procedure needs a larger quantity of epochs than the last one, because the error converges to zero at nearly 80 epochs.



**Figure 11.** Behavior of the Error for Supervised Training

The validation procedure of the training for the neural networks, shown in Figure 12, is achieved from the data registered from January to September of 2013, which has as result the UV index foreseen the same date of year 2014. The data is validated with the registered data taken from (14), obtaining a percentage of 66.8% of correct values over the totality of the information. According to the previous results, these kind of meteorological data compared with the information used in (21), does not have a behavior pattern defined, therefore through methods like Deep Learning, only an estimation close to values of the average UV index for the next year can be obtained.



**Figure 12.** Validation from January to September of 2014

With the given analysis, the algorithm is capable of predicting the meteorological variables values and the UV index for a given day if the information of the same date from previous years are available. The limitations of the application are given to the data from which the neural network is going to be trained. The more accurate and complete the information for the training is, the more reliable the application becomes.

In future applications, this algorithm could be upgraded to allow the user to know the exposure at immediate moments, instead of hours. As well to be implemented with other energy or solar based systems to provide even more data.

## CONCLUSIONS

The implementation of techniques of artificial intelligence like deep learning, allows develop applications, oriented to forecasting negative effects of solar radiation in human health, establishing relations between meteorological variables, and the natural conditions necessary to the appearance of this kind of adversities.

The ultraviolet index is found strictly related to the clear sky percentage at the moment of the data capture. For this reason, a better approach to foresee the time of sun exposure, necessary for generating a negative effect on the skin can be achieved, through the development of an application, using the concept of Hardware In The Loop. Where the meteorological data in real time were taken, and in this way foresee the UV index behavior for next day.

The necessary conditions for the appearance of an erythema depends directly of the skin features. Due to the previous, the possibility is set out to develop a study that allows compile information about meteorological conditions, necessary to generate these skin disorders for each of the six phototypes proposed by Fitzpatrick (16).

The techniques with deep learning architecture, based on multiple layers of neural networks, allow achieve a better approach to complex problems like the traffic flow prediction made in (21), and the prediction of health disorders, related with stochastic variables like the meteorological ones, over another techniques with limitations in their learning capacity, like Adaline (25) and Madaline.

## CONFLICT OF INTEREST

The authors like to confirm that there was no conflict of interest involved in the process of writing this manuscript.

## ACKNOWLEDGEMENT

This work has been supported by Vice-Rectorry of researches, Universidad Militar Nueva Granada, through project-ING 1576, year 2014.

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