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Analysis of the Reflectivity in Meteorological Radars using Data Mining and Neural Networks

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Abstract

Objectives: The aim of this work is show the analysis of the data measured by weather radar used in data mining and fuzzy logic. **Methods/Analysis:** A decoding of the data measured by the meteorological radar was made, which was encrypted, then an analysis of this data was made using neural networks that are trained with 10 and 20 neurons, in each case the effectiveness of each one is checked. **Findings:** The results showed that neural networks are an excellent tool that allows eliminate erroneous information and then normalize it to the scale used according to the standard. **Improvements:** This knowledge is essential for the aviation industry to operate properly and without risks for passengers, crew and aircraft, it is also important to anticipate and/or avoid, if possible, catastrophes generated by weather events related to rainfall.

Keywords: Data Mining, Neural Networks, Polarimetric Variables, Reflectivity, Weather Radar

1. Introduction

Radars have an important role in the field of meteorology. These devices send and receive signals that provide valuable information about the location and intensity of rainfall. Doppler radar technology goes far beyond the simple detection of reflectivity allowing obtaining high resolution data and estimated speed data, which is vital for short-term weather forecasting and weather prediction in severe conditions[1].

When looking at a radar image, an image of the distribution of precipitation (called an echo) and its intensity is sought. The radar echoes are represented graphically by a series of colored pixels, each color has an associated intensity scale that represents what is called the reflectivity in dBZ (reflectivity unit) and another scale that represents the corresponding rate of fall, which is an interpretation of light or heavy form precipitation. In winter season, this reflectivity is linked to the rate of snow fall in centimeters per hour (cm/h) and in summer months, the reflectivity is linked to the rainfall intensity in millimeters per hour (mm/h)[2].

The main difficulty in radar measurements is related to the diameter of the drops, that's why that the polarimetric radars are used. These have the ability to emit microwaves with double polarization, which incorporates new measurement variables, in addition to Z (reflectivity), called polarimetric variables, the specific phase difference (K_{DP}) and differential reflectivity (Z_{DR}). The first of these variables, K_{DP}, gives an estimate of the specific phase difference between the received signals.

This is achieved when the drops are large and is deformed generating a difference of optical paths between the radiation with horizontal and vertical polarization. On the other hand, Z_{DR} is defined as the quotient between the horizontal reflectivity Z_h and the vertical Z_v that the radar receives providing an estimate of the shape of the hydrometeors. This measurement shows that when Z_{DR} value is bigger, the drops will be bigger too and when Z_{DR} values are closer to one, smaller and more spherical they will be[3-8].

2. Data Preprocessing

The information generated by the weather radar is encrypted in a very particular format and it is necessary to use specific software applications to decode it and separate each of the variables generated by the radar.

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Commercially, there is a paid software application called Iris that allows the aforementioned decoding, the drawback of the application is its high costs. There is another free software application for Linux called RadX[9] that allows the decoding of data with similar results like the paid application; in this case RadX was used to obtain an array of data with each of the variables generated by the radar: Z_{DR}, K_{DP}, PHI_{DP} and RO_{HV}.

The decoded data have the following characteristics: 32-bit format with sign, without any type of unit. These characteristics are not suitable for the analysis or use of the data, so the transformation to standard units for each variable was necessary. For all cases the data must be presented as 8-bit unsigned values, so equation (1) was used for its initial treatment:

$$\frac{N+32767}{256} \quad (1)$$

N is the value decoded in 32-bit unsigned format by the RadX software.

Finally making use of the information related to the ranges of each variable in the user manual of the software Iris[10] are normalized and assigned units to each of the variables decoded and converted to 8-bit format with the Equations 2 to 6:

$$Z_{DR} = \frac{N-128}{16} \quad \text{Rank: -7.94 a +7.94 dB} \quad (2)$$

$$K_{DP} = 0.25 * 600\ \frac{N-129}{126} \quad \text{N >128 Rank: +0.250 a +142.58 degrees/Km} \quad (3)$$

$$K_{DP} = 0.25 * 600\ \frac{127-N}{126} \quad \text{N<128 Rank: -0.250 a −150.00 degrees/Km} \quad (4)$$

$$PHI_{DP} = 180 * \frac{N-1}{254} \quad \text{Rank: 0.0000 a 179.29 degrees} \quad (5)$$

$$RHO_{HV} = \sqrt{\frac{N-1}{253}} \quad \text{Rank: 0.0000 a 1.0000} \quad (6)$$

With this treatment, data matrices of 360 x 664 were finally obtained for each of the variables. It must be taken into account that when the obtained data are not valid or could not be measured in each case it is represented with values outside the range, for example, in the case of the variable Z_{DR} the invalid values are represented by the value 8 and the values where a measurement was not obtained, they are represented by the value -8.

3. Analysis of Reflectivity with Neural Networks

A neural network is defined with an input matrix of 360 x 664 which, as indicated above, corresponds to the size of the data generated by the weather radar, specifically for the variable Z_{DR}. With an output set that validates with a value 0 or 1 the possibility of rain in a specific area of the radar.

3.1 Training with 10 Neurons

The Figure 1 shows the representation of the neural network making use of the Neural Network tool of MATLAB, with the characteristics mentioned before, trained with 10 neurons and the time taken for this process.

As a result of the training, the margin of error can be seen in the histogram of Figure 2.

Finally it can be seen that the training for this particular case presents very good results giving a very high margin of confidence. Although the results with the simulation reflect a degree of confidence a little lower around 75% as shown in Figure 3.

Figure 1. Neural network with 10 neurons.

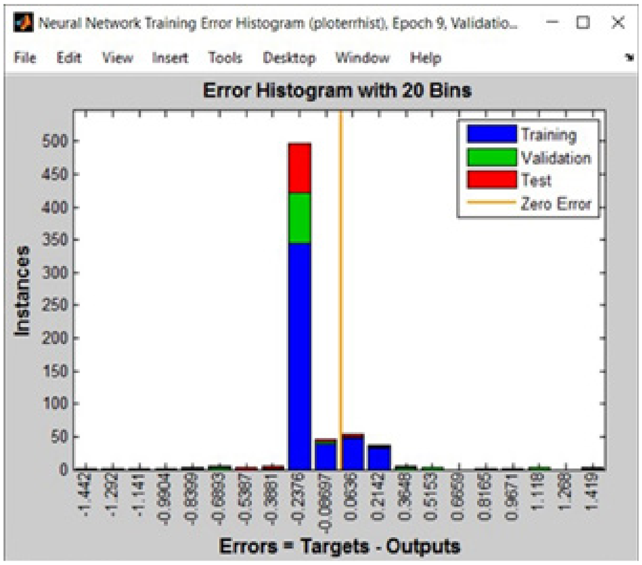

Figure 2. Margins of error of training with 10 neurons

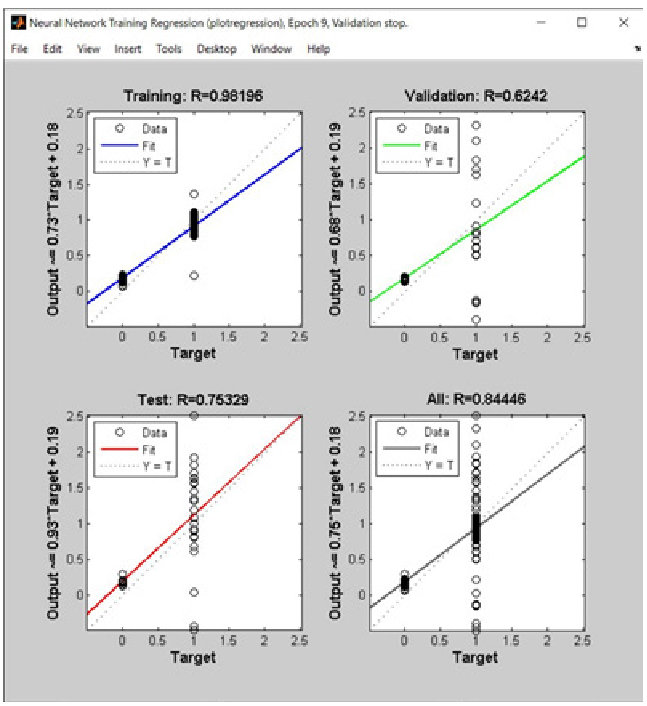

Figure 3. Result of training with 10 neurons.

3.2 Training with 20 Neurons

Given that the expected results were relatively low, the neural network is modified by training it with the same data and with 20 neurons, in Figure 4 the modified network and the time taken for the training process can be seen.

The error generated decreases with increasing number of neurons as can be seen in the graphs of Figure 5.

The training with 20 neurons presents better results than 10% of the cases with a confidence level of 90% as shown in Figure 6.

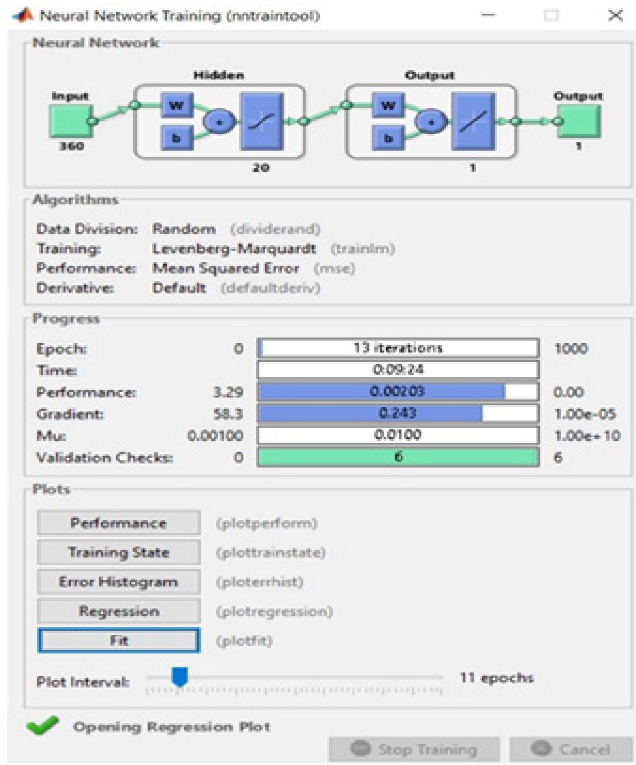

Figure 4. Neural network with 20 neurons.

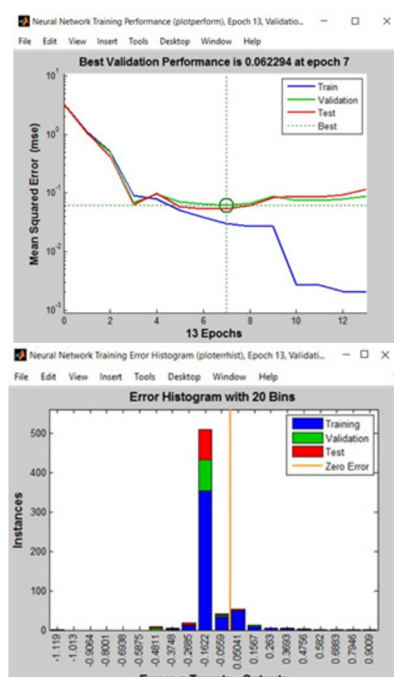

Figure 5. Error margins of training with 20 neurons.

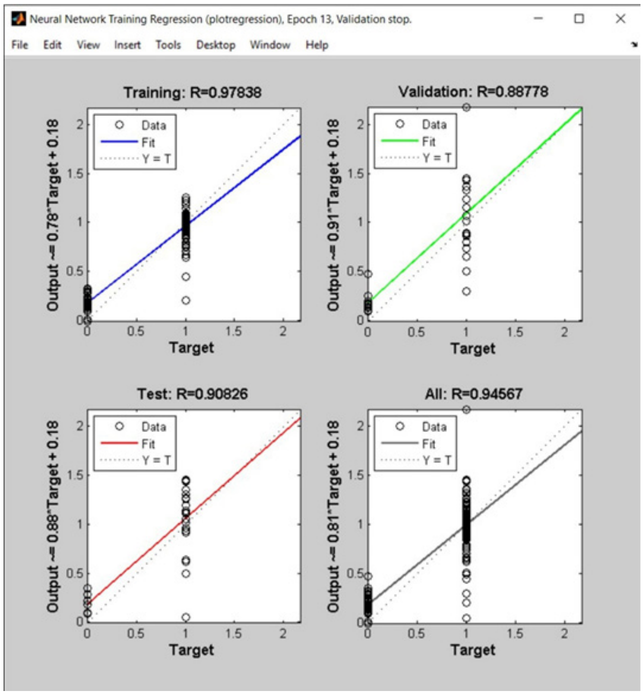

Figure 6. Result of training with 20 neurons.

4. Conclusion

To perform any type of data analysis, the most important and normally and time-consuming process is reprocessing and adjusting the data for this, there are several tasks and methods. In the case of the work done with the radar data it was necessary to carry out an initial decoding process to decrypt them, then transform them into an appropriate format, clean them by eliminating erroneous information and normalize them to the scale used according to the standard.

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