Reconstruction of Severe Storms Observed by Weather Radars Using Convolutional Neural Networks

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INTRODUCTION

Severe storms events with tornadoes can cause destruction and significant loss of life. Analyze the formation and structure of these systems helps to identify the favorable conditions for their generation, contributing to specific techniques for prediction. One way to observe these storms is through weather radar. They have one of the most accurate and used technologies within meteorology, and it is the only instrument capable of observing the three-dimensional structure of the clouds, providing this data with high spatial and temporal resolution.

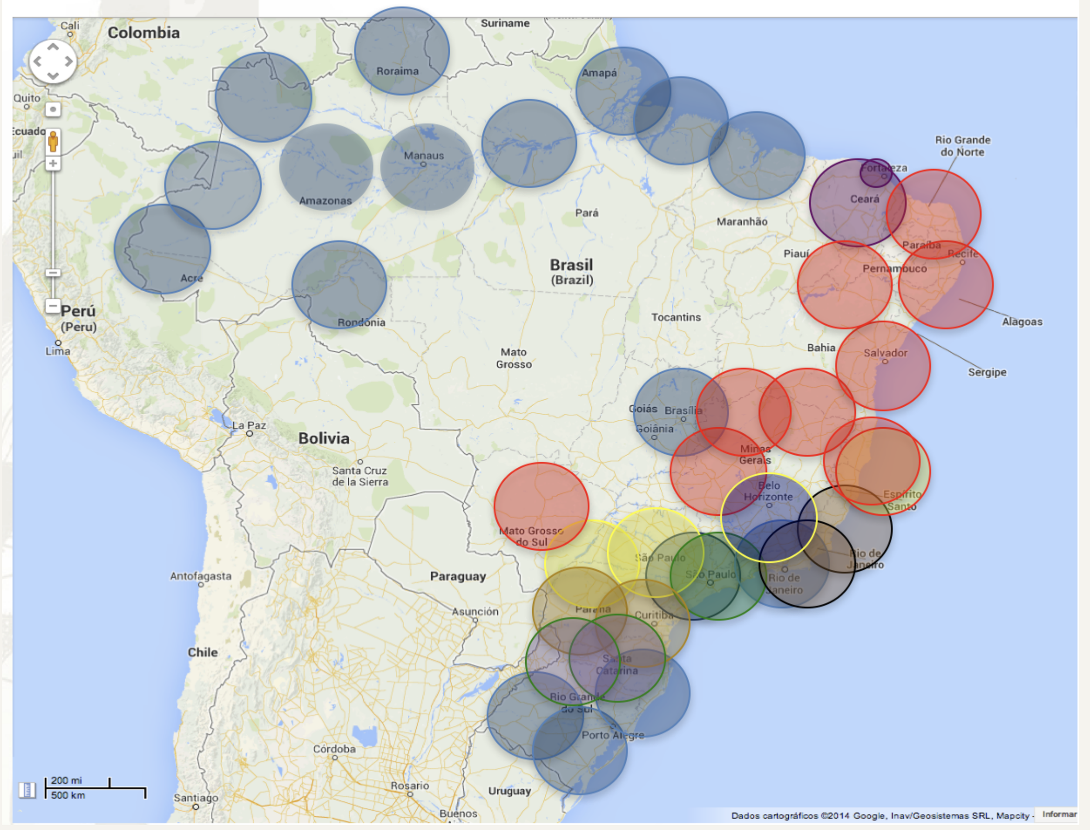
In the past 10 years, we increased our weather radar coverage in Brazil from 23 single polarization to 19 more new dual polarization radars (Fig. below, left), mainly S-Band, with a concentration in the southern region, an area prone to severe weather, mostly related to Mesoscale Convective Systems. The major economical activity in this region is agriculture and energy production, responsible for more than 35% of hydro power energy generation used in the country, directly dependent on precipitation distribution, water availability and severe storms impacts.

Weather radars in southern Brazil play an important role in quantitative precipitation estimation and severe weather monitoring and forecasting. Usually, these storms are accompanied by the occurrence of atmospheric discharges, which can cause energy distribution problems and shutdowns in the electric sector.

The operational volume coverage pattern for this network has an update cycle every 10 minutes. However, it is not uncommon to lose information from severe weather events occurring in between this update cycle.

Parana State has three meteorological radars operated by the Parana Meteorological System (SIMEPAR), two S-Band and one X-Band. One of them, located in Cascavel - PR, (Fig. below, right) is an S-Band Radar with Dual Polarization and performs measurements in an area up to 240 km range, monitoring rainfall in the west region of Paraná. However, the scans performed by this radar have intervals of 5 minutes and, as a storm dissipate quickly, it may not be possible to observe its complete evolution through these data.

The purpose of this paper is to use recurrent neural networks to create a continuous visualization of weather radar data. This approach will allow us to study the dynamics of these systems by focusing on the analysis of their physical parameters such as life cycle and volume.



Brazilian Weather Radar Network

Parana State West Weather Radar.

DATA AND METHODOLOGY

In this preliminary study, we used the weather radar data from 01.01.2018 to 11.01.2019, comprising 23 month of data, and also Total Lightning data from the National Lightning Detection Network (RINDAT, http://www.rindat.com.br), for the same period.

For the CNN network input layer, Total Lightning density and polarity were used, together with weather radar reflectivity only - no polarimetric variables were used. Reflectivity values below 20 dBZ were filtered to eliminate clutter. Both data were interpolated to a regularly spaced grid with horizontal resolution of 3x3 km and temporal resolution of 5 minutes (minimum monitoring interval available). Electric discharges are used because they are strongly related to intense precipitation. These data were divided into three parts: 50% for training, 20% for validation and 30% for network testing.

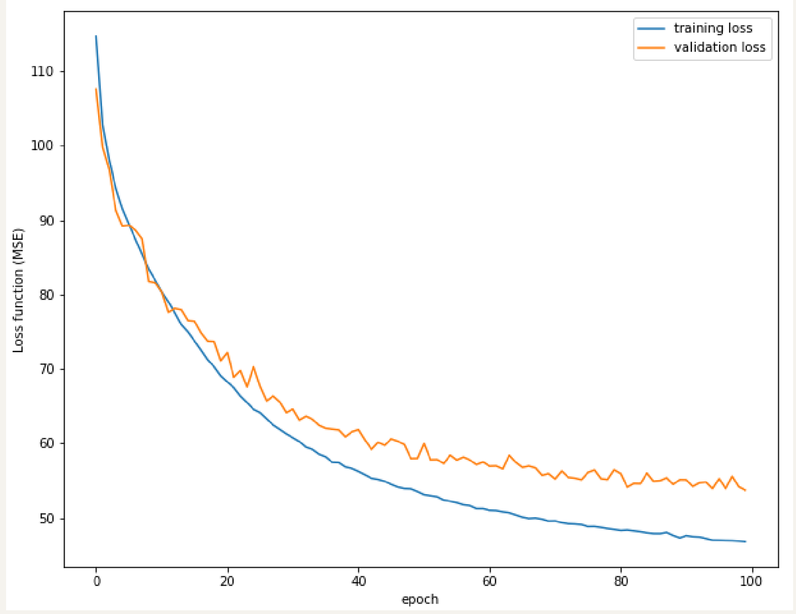
A Convolutional Neural Network (CNN) is a variation of the Multilayer Perceptron Networks (MLP) and has been inspired by the biological process of visual data processing. Similar to traditional computer vision processes, a CNN is able to apply filters to visual data while maintaining the neighborhood relationship between image pixels throughout network processing. This type of network has been widely used, mainly in the classification, detection and recognition applications in images and videos.

A CNN can be divided into two parts: feature extraction by convolutional layers and a traditional neural network (in this work, MLP was used). Convolutions are operations between arrays that are applied multiple times to different regions of the image, changing the representation of the data and learning the filters. Filter weights are automatically calculated and each filter learned is a feature puller.

The CNN architecture used has three convolution layers where all use 3x3 filter size 32, 64 and 128, respectively. Each convolution layer has a max-pooling layer that decreases the convolution matrix of each step, taking the largest value from each convolution matrix (uses 2x2 filters and have the same size as the convolution layers).

After the feature extraction step, the matrix was transformed into one-dimensional, obtaining 102400 representation variables. The last step was the application of MLP, which contains a dense network of 512 neurons and the output layer has 25600 values, which represent the reflectivity image.

After CNN training and validation, we analyzed if there were any problem of overfitting. This occurs when a neural network captures the noise of its database, thus losing the power of generalization. We can evaluate this situation by graphing the training and validation loss function. If the lines diverge, there is an overfitting problem, and when they fall together, the network is learning. In the case of the CNN created, there was no overfitting, as shown in the figure below, because this divergence between training and validation tends to occur after 100 epochs, which was not the case with this network.



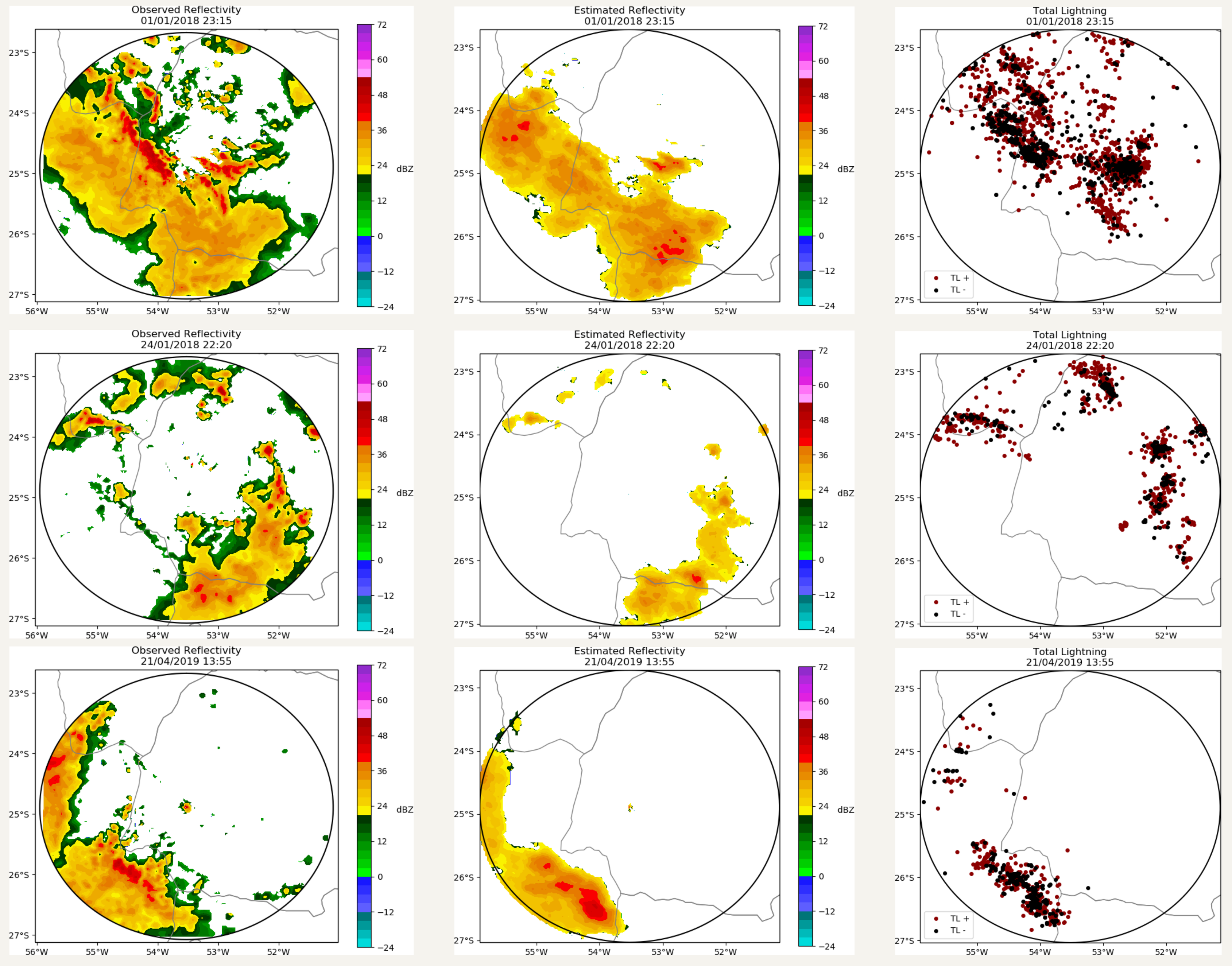
Learning curve for the CNN algorithm.

RESULTS

The results obtained by the CNN were evaluated through BIAS (estimated value - observed value). We also used the correlation coefficient between the estimated and observed data, which describes the association or dependence between the two variables, where the values vary between 0 and 1 and the closer to 1, the greater the correlation. Results are presented in the table below.

BIAS	-0.42
Correlation	0.75
R^2 (Coefficient of Determination)	0.17

Negative BIAS indicates that the estimated reflectivity data is below the observed values, as shown in the figures below.



Observed Reflectivity — Reconstructed Reflectivity — Total Lightning

CONCLUSION

The CNN results provide a good estimate of the storm regions in the radar area, although the intensity of the reflectivity values reconstructed were lower than the observed. These lower reflectivity values show that, for future work, more characteristics should be obtained, therefore improving the reflectivity reconstruction because the problem is not linear and only two characteristics were not sufficient to produce better results.