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Recurrent Neural Networks applied to short-term weather forecasting using radar images from the city of Chapecó, SC, Brazil

Redes Neurais Recorrentes aplicadas a previsão de curto prazo utilizando imagens de radares da cidade de Chapecó - SC

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ABSTRACT

This work proposes a new computational approach that makes use of Recurrent Convolutional Neural Networks, in which weather radar images are used to predict the spread and intensity of storms up to 3 hours in advance, known as nowcasting. To this end, we used images from the meteorological radar located in the city of Chapecó - SC. This data is public and available on the website of the Institute for Space Research (INPE). To this end, we propose to evaluate the use of a recurrent convolutional neural network with spatiotemporal learning called PredRNN++. The results were validated through case studies of storms that occurred in the region covered by the radar. To evaluate the performance of the neural network, in addition to a visual analysis of the results, the MSE and SSIM metrics were used. The results show that PredRNN++ was able to simulate the shape and location of the weather system.

Keywords: Recurrent neural networks; Nowcasting; Radar; Meteorology

RESUMO

Neste trabalho propõe-se uma nova abordagem computacional que faz uso de Redes Neurais Convolucionais Recorrentes, na qual imagens de radar meteorológico são utilizadas para a previsão de propagação e intensidade de tempestades com até 3h de antecedência, conhecida como nowcasting. Para tal, utilizou-se imagens do radar meteorológico localizado na cidade de Chapecó-SC. Esses dados são públicos e estão disponíveis no site do Instituto de Pesquisas Espaciais (INPE). Para isso é proposta a avaliação do emprego de uma rede neural convolucional recorrente de aprendizagem espaço temporal chamada PredRNN++. Os resultados foram validados através de estudos de casos de tempestades ocorridas na região de cobertura do radar utiliza. Para avaliar a performance da rede neural, além de uma análise visual dos resultados, foram utilizadas as métricas MSE e SSIM. Os resultados mostram que a PredRNN++ foi capaz de simular o formato e local onde ocorreu o sistema meteorológico.

Palavras-chave: Redes neurais recorrentes; Nowcasting; Radar; Meteorologia

1 INTRODUCTION

One of the most important fields within meteorological studies is weather forecasting, which encompasses an analysis of historical data, real-time observations and numerical models to predict the atmospheric conditions of a given region of the globe. Among the most varied types of forecasting, one of the most important can be called nowcasting, which focuses on predicting weather conditions in a short period of time in the future (less than three hours) (Browning, 1989).

Among the techniques used for nowcasting, the analysis of recent meteorological trends and statistical forecasts based on historical atmospheric data have always been the most widespread in academia. Putting these atmospheric variables together in a numerical forecasting model aims to provide the meteorologist with a forecast over a short period of time that will be useful in emergency situations, such as storms, tornadoes, heavy rains and other extreme weather conditions usually form over this short period of time. However, there are problems with classic nowcasting methodologies.

According to Camporeale (2019), numerical prediction models do not have high precision for the mentioned events above and make forecasting them difficult. In view of these difficulties in terms of accuracy, meteorological forecasting techniques have been developed in recent years that make use of images from meteorological radars in order to find viable alternatives for nowcasting and consequently improve the forecasting capacity for this type of event.

In academia, among various methodologies, Recurrent Convolutional Neural Networks (RCNN) have shown satisfactory results in predicting image sequences, using spatiotemporal learning. This approach allows the network to analyze the data sequences and extract the characteristics that make them up, enabling future predictions to be made. According to Wang (2018), RNCRs are particularly suitable for the type of problem addressed in this work.

In view of the above, this work aims to evaluate the applicability of Recurrent Convolutional Neural Networks in weather forecasting, using reflectivity data obtained from the Chapecó, SC, Brazil, weather radar. This radar was chosen due to the availability of quality images with a good time interval, allowing the network to be trained properly. We believe that recent machine learning techniques have great potential for analyzing atmospheric processes and could become an interesting alternative for nowcasting in Brazil.

2 METHODOLOGIES

As mentioned above, for this work we used images obtained by the radar of the city of Chapecó, which has an altitude of 3km, a range of 250km and is located at coordinates 27° 02 ‘52.7”S 52° 36’13.3 “W. The Radar specifications and the data (images) used in this work are available on the website of the Brazilian National Institute for Space Research (INPE).

Figure 1 – The radar used

Radar coverage used in the southern region of Brazil

Source: Google Maps (2023)

The Neural Network chosen for this work was PredRNN++, which is a network developed by Wang (2018). PredRNN++ is a Recurrent Convolutional Neural Network optimized for spatiotemporal prediction, which uses images sequenced in time to predict new images that continue the sequence. This type of sequential prediction is exactly what the problem we are trying to solve needs, since the readings from weather radars are in exactly the same format. The network is composed of two structures: the first is the Causal LSTM, which is responsible for capturing the complex dependencies and variations in the data sequence, as shown in figure 2. The second structure is the Gradient Highway Unit (GHU), whose function is to maintain the stability of the gradients during training of the network.

Figure 2 – PredRNN++ structure

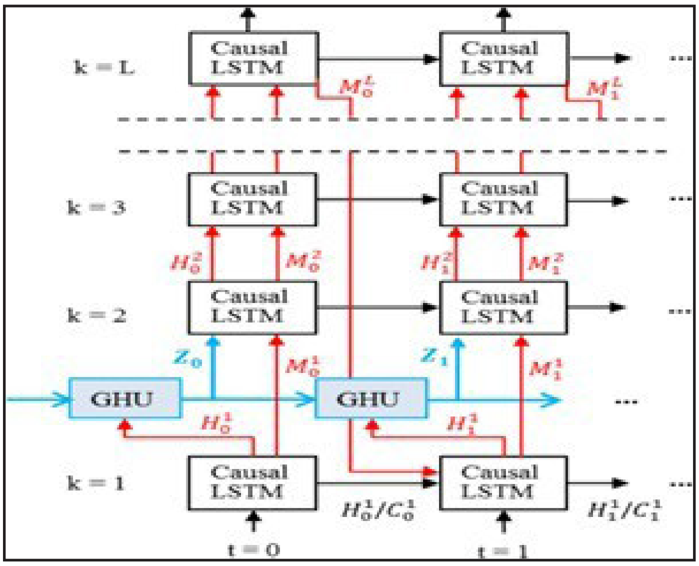


Diagram with the complete structure of the neural network used

Source: Wang (2018)

Still on the structure of the network in figure 2, t represents the time step the network is in, k represents the model's last hidden layer, M_t^k and C_t^k represent spatial memory and temporal memory respectively, H_t^k is the final output of the neural network and Z_t the intermediate state of the network provided by the GHU. The blue connections represent the GHU units, connecting the current step to previous inputs, while the red connections show the connections in the deeper layers of the network (Wang, 2018).

To evaluate the quality and accuracy of the neural network, two metrics were used. The MSE (Mean Square Error) presented by Hyndman (2006) and the SSIM (Structural Similarity Index) presented by Wang (2004). Both metrics are also used in the original PredRNN++ tests and constantly used in other predictive models using neural networks. MSE was used to train the network and SSIM was used to analyze the results generated.

The neural network was trained using 20,000 radar images from Chapecó, representing reflectivity data from random moments between January 2020 and March 2022. The images were organized into 1,000 sequences, each containing 20 images. Of these sequences, 800 were used to train the network and 200 were used for validation. According to the structure of PredRNN++, the 20 images within each sequence represent the input for the previous 50 minutes (10 images), which are used to predict the next 50 minutes (10 images). It is important to note that the radar used takes readings every 5 minutes, which explains the specific duration of each sequence.

PredRNN++ has a predefined standard structure that makes use of 64x64 pixel grayscale images. As the images provided by the radar are 500x500 pixels in size and are in color, it was necessary to convert and resize the images to the network's standard.

The process of training convolutional neural networks is generally more demanding in terms of computing power than classical neural networks. Therefore, for this work, the network was trained using an NVIDIA Tesla P100 video card provided by the Google Colab cloud service. The network was trained by 30,000 epochs and took around 100 hours to complete. After training, the network takes between 30 and 45 seconds to generate a prediction.

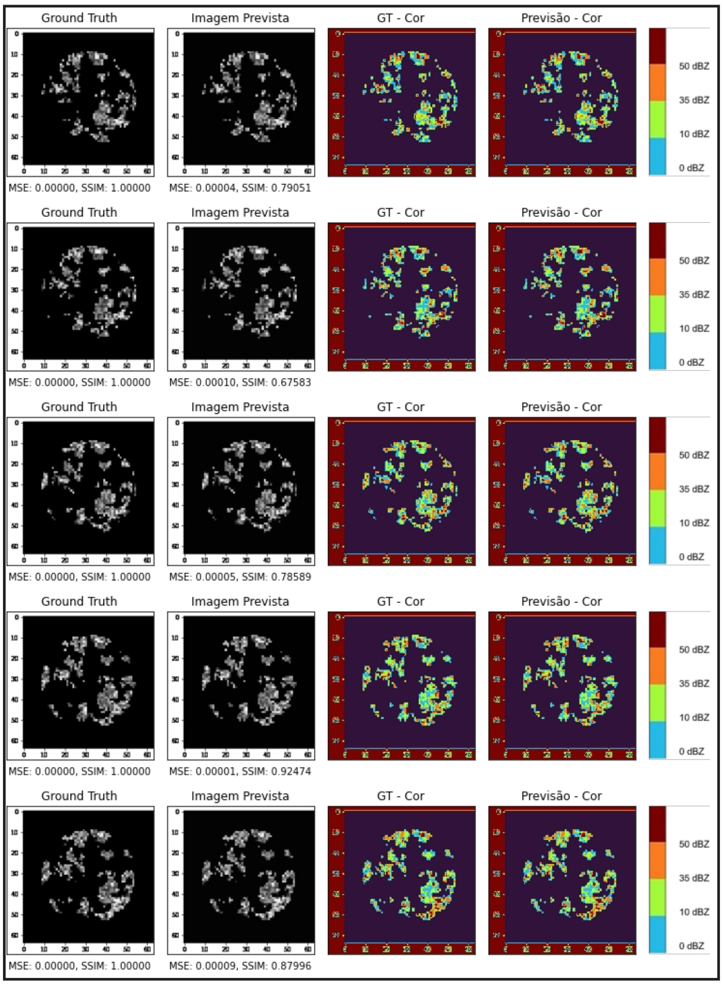
3 RESULTS AND DICUSSIONS

In order to analyze the neural network's predictive capacity, we selected a meteorological event that occurred in the area covered by the radar on March 25,

2023. On that day, heavy rain, winds over 60 km/h and flooding were recorded in the region of the city of Chapecó, SC, Brazil. It is worth noting that this data was not included in the network's training set.

The images presented to the network correspond to the time interval between 7:06 p.m. and 8:56 p.m. on the day in question (a total of twenty images). The ten images corresponding to the time period from 7:06 p.m. to 8:01 p.m. were used as input for the neural network and the remaining ten images (8:06 p.m. to 8:56 p.m.) are the Ground Truth of our problem, i.e. the target we are trying to predict.

Figure 3 – Results from the first half of the forecast

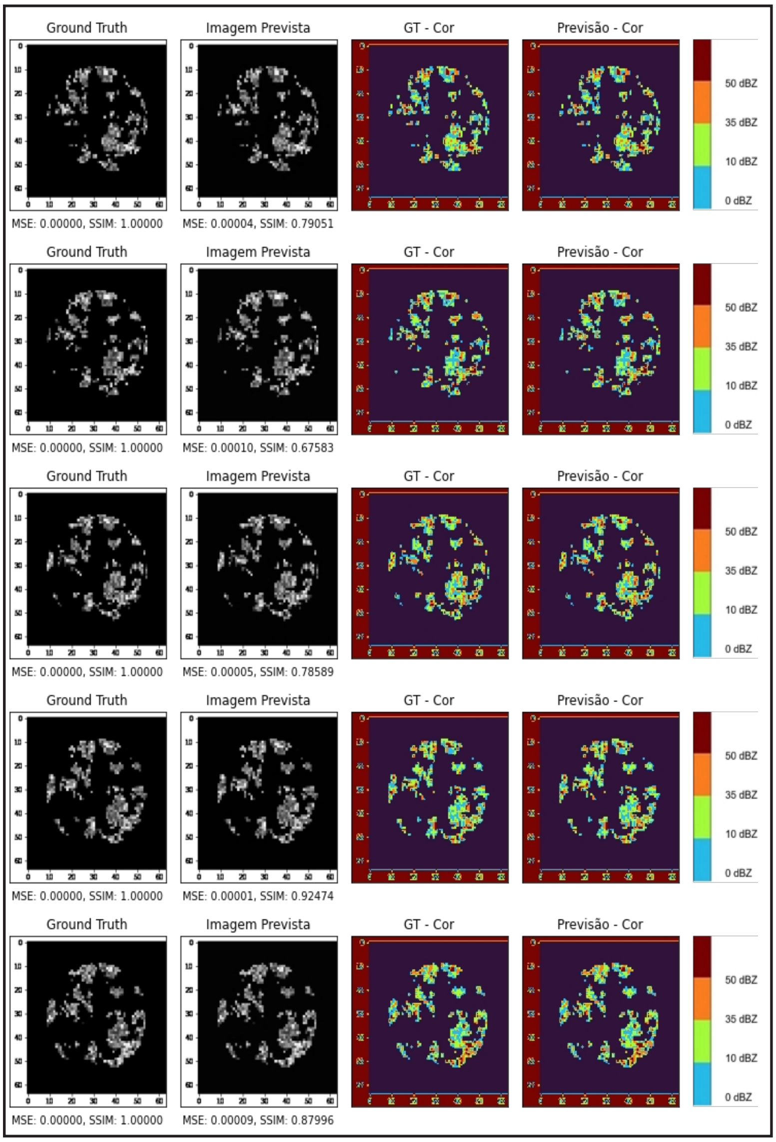


Generated forecast for the first 25 minutes, between 8:06 p.m. and 8:26 p.m.

Source: Authors (2023)

The results obtained are shown in figure 3 and figure 4. Each of the figures contains 5 rows, which represent each of the time moments captured by the radar (every five minutes) and four columns, which represent the ground truth (target) and the prediction generated by the network, both in grayscale and in color. In addition, each of the forecasts shows the calculation of the MSE and SSIM metrics.

Figure 4 – Results from the second half of the forecast



Generated forecast for the last 25 minutes, between 8:31p.m. and 8:56 p.m.

Source: Authors (2023)

A subjective and visual analysis of the forecasts generated shows that PredRNN++ is able to simulate the shape and location of the weather system with great accuracy. In addition, the intensity of the system is represented in a way that is very faithful to the ground truth. Overall, the ten predicted images had a global SSIM of 0.85347, which represents a very high similarity between the predicted image and the ground truth.

4 CONCLUSIONS

Predicting future weather conditions is crucial for society, and improving the ability to forecast extreme phenomena such as storms, floods and strong winds is even more important to avoid material losses and, above all, loss of human life.

This study demonstrates that Recurrent Convolutional Neural Networks can be excellent tools for predicting extreme weather events and helping to prevent possible damage caused by them. Even though it's an area of research that's not extensively explored in Brazil, this work presents very promising results using the available data.

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