Precipitation Nowcasting Using Deep Learning with Pixel Classification

Taisong Xiong¹,²,³, Haicong Li¹, Zhu Li⁴ and Yuanyuan Huang³,*

¹ School of Computer Science and Engineering, University of Electronic Science and Technology of China, Chengdu 611731, PR China
² CMA. Key Laboratory of Atmospheric Sounding, Chengdu 610225, Sichuan, PR China
³ Chengdu University of Information Technology, Chengdu 610225, Sichuan, PR China
⁴ China Mobile Group Sichuan Co. Ltd., China

*Corresponding author e-mail: iyyhuang@hotmail.com

Abstract. Accurate nowcasting of heavy rains can effectively mitigate damages following meteorological disasters. Precipitation nowcasting—an important tool for forecasting rainfall intensity, has become a challenging topic of study for many meteorologic researchers. In recent years, precipitation nowcasting models based on deep learning have been receiving more attentions. In this study, an encoder-forecaster framework model is proposed for precipitation nowcasting. In this model, sufficient feature map numbers are given in every layer to effectively capture the spatiotemporal features of radar echo sequences. The mode of prediction differs traditional radar echo extrapolation methods, which only yields radar echo intensity values, while the proposed model obtains the pixel classifications. Significant improvements were attained by the proposed model for the two highest radar echo intensity levels compared to the traditional model. The extrapolation results demonstrate the effectiveness and accuracy of the proposed model for precipitation nowcasting.

1. Introduction

Precipitation nowcasting typically refers to precipitation forecasting within 0 to 2h following modeling. Weather radar is the most effective and reliable nowcasting tool. Studying the evolution of radar echo images, we can evaluate changes in echo, direction of movement, and range of influence of nearby weather systems. However, the evolution trend of regional convective weather exhibits strong irregularities, which hinders facile forecasting. Numerical prediction (NWP) models [1] are often not effective in this context, and the traditional radar echo extrapolation methods commonly used in operations often exhibit large deviations. Convective weather may cause severe losses to human life and infrastructure. Therefore, accurately predicting convective weather processes has become the focus of current research on meteorological disaster and prevention [2].

Two methods are widely applied to contemporary precipitation nowcasting - NWP model and radar echoes extrapolation [3, 4]. The NWP model has been successfully applied to several meteorological fields owing to its ability to simulate complicated physical rules of the atmosphere and to
predict weather information over long periods. However, its real-time utility and accuracy cannot meet the needs of precipitation nowcasting. Conversely, the extrapolation method is faster and more accurate than NWP modeling for precipitation nowcasting [5] and has become the preferred method. Radar echo extrapolation was first put forth by Rinehart R E [6] who proposed a method called tracking radar echoes by correlation (TREC) to extrapolate the positions and intensities of radar echoes. TREC has been widely applied to precipitation nowcasting [7, 8] because of its simplicity of implementation and speed. To obtain the optical flow field of radar echoes, an optical flow model [9] has also been applied extrapolation of radar echoes. Precipitation nowcasting has undergone significant changes, these methods require further to be improved.

In recent years, with the development of big data [10] and improvement in the computational ability of graphics processing Units (GPUs), deep learning [11, 12] has become topic of significant interest for academic and industrial applications. Inspired by some successful applications of long short-term memory (LSTM) models [13, 14], Shi et al [5] proposed a convolutional LSTM network (ConvLSTM), a pioneering model for precipitation nowcasting. ConvLSTM uses the encoder-decoder framework proposed by Sutskever et al [14]. The ConvLSTM model seamlessly integrates convolutional operation into LSTM and effectively captures the spatiotemporal features of the radar echo sequences. The inputs of the encoder network are the current radar echo sequences, and the output of the decoder is the prediction of the following echo sequences. The experiments reported by Shi et al [5] demonstrate that deep learning has significant potential for meteorological research applications. Following the implementation of ConvLSTM, other models have been proposed for precipitation nowcasting. A predictive recurrent neural network (PredRNN) has also been proposed [15] to extrapolate the radar echo. The strength of PredRNN is that it learns the temporal variations and spatial appearances of radar echo sequences using a unified memory pool. To increase the recurrence depth and prevent gradient back-propagation of PredRNN, an improved network called PredRNN++ [16] model was proposed, which obtained better results. To improve the representation of the location-variant relationship for convolutional operation, a trajectory gated recurrent unit (TrajGRU) model was proposed [17]. To enhance the non-stationary modeling capability of this method and further improve the precision of precipitation nowcasting, a memory in memory (MIM) model [18] has been proposed. The MIM model substitutes the forget gate of LSTM with two embedded long short-term memories to model spatiotemporal non-stationarity.

Although there have been several advances in meteorological deep learning in recent years, existing models require further improvement. In this study, a model based on the encoder-forecaster framework for precipitation nowcasting was proposed. More feature map numbers were set in each layer of the proposed model. Determining a sufficient number of features in each layer can ensure the effective capture of spatiotemporal features of the radar echo sequences and yield the more precise prediction results. Compared with some radar echo extrapolation models, the classifications of echo pixels were obtained rather than the intensities of pixels. Therefore, the regression problems of radar echo extrapolation were transformed into classification problems. Then other methods were adapted to capture the features of radar echoes and improve the precision of the extrapolated results. The core of the proposed model is that there are down-sampling layers and three RNN layers for the encoder network, moreover, three up-sampling layers and three RNN layers for the forecaster network. The function of the down-sampling layer of the encoder network is to reduce the size of feature maps and facilitate to capture higher level semantic features. The three up-sampling layers were used to increase the size of feature maps and restore the size of images. The function of the three RNN layers in both the encoder network and the forecaster network is to capture the spatiotemporal features of radar echo sequences. The RNN layers play a kernel function for sequence forecasting.

The remainder of this paper is organized as follows. In Section 2, the background of precipitation nowcasting is discussed in detail. We present the proposed model and analyze the functions of the network in Section 3. Quantifiable experimental results are presented in Section 4. Conclusions are presented in Section 5.
2. Background On Precipitation Nowcasting

Based on the previous radar echo sequence, precipitation nowcasting forecasts the following radar echo sequence at a fixed length. In general, a radar echo map is obtained using a weather radar every 6 min. For precipitation nowcasting, there are $L$ radar echo maps in one sequence each time. The size of the radar echo maps is $M \times N$. We use a tensor $Z^{L \times M \times N}$ to represent a sequence $Z_1, Z_2, ..., Z_L$. Precipitation nowcasting is used to forecast the following most probable length-$T$ sequence given a fixed length-$Q$ radar echo sequence.

$$
\tilde{Z}_{t+1}, \tilde{Z}_{t+2}, \ldots, \tilde{Z}_{t+T} = \arg \max_{Z_{t+1}, \ldots, Z_{t+T}} P(Z_{t+1}, \ldots, Z_{t+T} | Z_{t+Q+1}, Z_{t+Q+2}, \ldots, Z_t).
$$

Precipitation nowcasting can be treated as a spatiotemporal sequence forecasting problem for machine learning. In general, the results of precipitation nowcasting based radar echoes are a 2D radar echo sequence and their measurements are the intensities of the radar echo. Precipitation nowcasting is performed at the pixel level. According to the Z-R relationship, radar echo intensities and the levels of rainfall have a corresponding relationship. Therefore, the radar echo intensities can be translated into the levels of rainfall. Thus, precipitation nowcasting becomes a classification problem from a regression problem.

3. Proposed Model

In this section, a model for precipitation nowcasting using pixels classification was proposed. As in the aforementioned models, the results of precipitation nowcasting are radar echo intensities. The values of radar echo can be translated into rainfall intensity according to the Z-R relationship. The network architecture of the proposed model is shown in Fig 1. A similar encoder-forecaster structure [17] was adopted to extrapolate the radar echo sequence. A sequence of 10 radar echo maps is fed into the encoder networks. Then, the forecaster networks predict the following 20 consecutive radar echo maps. Three down-sampling layers and RNNs layers were inserted into the encoder network. RNNs can be any RNN operation. With the exception of 3 up-sampling layers and RNNs layers in the forecaster network, a $1 \times 1$ convolution operation layer is adopted to reduce the number of feature maps and capture the representative features of the data. Unlike many existing radar echo extrapolation models, this model obtains the pixel classifications of radar echo frames rather than the pixel intensity. Therefore a 6-way softmax layer was added to classify the pixels of the radar echo frames. The extrapolation results are then obtained as echo pixel classifications.

![Figure 1. Architecture of proposed encoder-forecaster network for precipitation nowcasting](image-url)
As depicted in Fig 1, the encoder network contains six layers with weight values. Three RNN layers following every convolutional layer capture the spatiotemporal features of the radar echo sequence, and the size of their outputs is the same as their inputs. Long distance convolutional operations can effectively capture higher-level semantic features. Hence, the appropriate feature maps can learn the inherent spatiotemporal relationships of the radar echo sequence. There are three RNN layers in this network, and the RNN layers do not change the sizes of their inputs. The sizes of the layer outputs are the same as those of their inputs. The values of the hidden states and cell states of the RNN layers are closely related to its proceed RNN. Following the third RNN layer, the size of the up-sampling layer’s input is 16×16×512. The sizes of the kernels of the 1st and 2nd up-sampling layers are 4×4×512 and 4×4×256, respectively, both with strides of 2 pixels. The two up-sampling layers enlarged the input double. The third up-sampling layer has 64 kernels of size 6×6×128, and the size of its output is 256×256×64. A 1×1 convolutional layer is added to make the feature maps of size 256×256×6 to classify the pixels of the radar echo. Then, a softmax layer is used to obtain the pixel classification. The proposed model so obtained is called as prediction and classification model (PredClassification). In this model, any type of RNNs can be chosen for the RNN layers. To effectively capture the spatiotemporal features of the radar echo sequences, we selected the TrajGRU [17] for the RNN layers.

4. Experiments

The resolution of real radar echo dataset is 256×256. The proportion of strong intensity radar echo values is very high in this dataset. Therefore, it is more challenging to correctly extrapolate the radar echo sequences. We translated the raw radar reflectivity factors to pixel values and clipped the values of pixels between 0 and 255 using the following equation.

\[
\text{pixels} = \left\lfloor \frac{255 \cdot \text{dBZ}_{\text{pixels}} + 10}{90} \right\rfloor
\]

4.1. Evaluation Criteria

For results quantification, two criteria were adopted to verify the effectiveness and robustness of the proposed model: the critical success index (CSI) and probability of detection (POD), respectively. There are 5 classes of pixels in the radar echo images according to their intensities: intensities between 0 and 20, 20 and 30, 30 and 40, and 40 and 50 are classified as the first, second, third, and fourth classes, respectively. Intensities larger than 50 are classified as the fifth class. The prediction results (we used prediction to represent it) were obtained by the model. The real results were obtained using the ground truth. For the kth class (k=1, 2, ..., 5), we calculated hits(prediction=k, ground truth=k), false alarms (prediction=k, ground truth != k) and misses(prediction=j, ground truth=k, j!=k). The formulae of the two criteria are given as follows, respectively. Larger CSI and POD values indicate better results.

\[
\text{CSI} = \frac{\text{hits}}{\text{hits}+\text{falsealarms}+\text{misses}}.
\]

\[
\text{POD} = \frac{\text{hits}}{\text{hits}+\text{misses}}.
\]

4.2. Evaluation Algorithms

To verify the effectiveness of the proposed model, three state-of-the-art models based on deep learning were employed. They are ConvLSTM in [5], ConvGRU in [5] and TrajGRU in [17], respectively. The network structures used were the same as those used in [17]. The encoder network is composed of three convolutional layers and three RNN layers. The forecaster network is composed of three up-sampling layers and three RNN layers. The numbers of kernels of the encoder-forecaster network were the same as those set in [17], and the size of the kernels is the same as that of our proposed model. The training batch is set to 2 throughout the experiment.
4.3. Quantitative Evaluation

| Algorithm | ConvLSTM | ConvGRU | TrajGRU | PredClassification |
|-----------|----------|---------|---------|--------------------|
| $0 \leq \text{dBZ} \leq 20$ | 0.853 | 0.851 | 0.855 | 0.874 |
| $20 < \text{dBZ} \leq 30$ | 0.256 | 0.257 | 0.258 | 0.238 |
| $30 < \text{dBZ} \leq 40$ | 0.338 | 0.341 | 0.345 | 0.353 |
| $40 < \text{dBZ} \leq 50$ | 0.218 | 0.208 | 0.227 | 0.225 |
| dBZ > 50 | 0.062 | 0.046 | 0.075 | 0.096 |

To quantitatively evaluate the experimental results, two criteria aforementioned CSI and POD were adopted to evaluate the experimental results. The corresponding values obtained by all models are given in Table 1 and 2, respectively. For CSI and POD, the proposed model obtained higher values than other models for most thresholds. In particular, for the two highest intensity thresholds, the differences between the proposed model and TrajGRU are significant at 0.11 and 0.074 for POD, respectively. This demonstrates that the proposed model improved prediction of the radar echo strong intensity values, which is crucial for forecasting convective weather. However, the CSI obtained by the proposed model is relatively higher than other models in several thresholds. In other words, the correctness and robustness of the proposed model are better than those of the other models.

| Algorithm | ConvLSTM | ConvGRU | TrajGRU | PredClassification |
|-----------|----------|---------|---------|--------------------|
| $0 \leq \text{dBZ} \leq 20$ | 0.901 | 0.898 | 0.901 | 0.940 |
| $20 < \text{dBZ} \leq 30$ | 0.424 | 0.419 | 0.427 | 0.300 |
| $30 < \text{dBZ} \leq 40$ | 0.591 | 0.596 | 0.606 | 0.612 |
| $40 < \text{dBZ} \leq 50$ | 0.335 | 0.320 | 0.340 | 0.450 |
| dBZ > 50 | 0.076 | 0.062 | 0.095 | 0.169 |

5. Conclusion

Based on deep learning, an encoder-forecaster model was proposed and applied to real data for verification. The proposed model obtained better radar echo extrapolation results than some state-of-the-art deep learning models. Firstly, an effective number of feature maps were adopted in each layer to capture the spatiotemporal features of radar echo sequences and improve prediction accuracy. Secondly, the proposed model predicted the pixel’ classifications instead of the pixel’ intensities, thus obtaining more precise extrapolation results of echo intensities, which leads to improved strong convective nowcasting.

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