Tiny-RainNet: A Deep CNN-BiLSTM Model for Short-Term Rainfall Prediction

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Key Points:

- We propose a Tiny-RainNet model for rainfall prediction based on sequential radar maps and CNN-BiLSTM.
- Optimal size of input radar maps of Tiny-RainNet is determined by combining temporal-spatial information.
- Tiny-RainNet is superior to existing ConvLSTM, LSTM, FC-LSTM, and AlexNet based on CIKM AnalytiCup 2017 dataset.

Abstract

A data-driven short-term prediction model called the Tiny-RainNet model is proposed to reduce the cumulative errors caused by multi-step prediction and the complexity of other models. We attempted to improve the accuracy of Doppler radar detection of short-term rainfall prediction using different radar echo maps and numerical model prediction. Rainfall prediction is a complicated temporal- spatial problem. Combined with the convolutional neural network in extracting image context information and the advantages of Bi-directional Long Short-Term Memory (BiLSTM) in processing timing information, 60×10×10 sequential radar echo maps were used as the input of Tiny-RainNet to predict the rainfall in the next 1 to 2 hours.. The proposed Tiny-RainNet, with a root mean square error (RMSE) of 9.67 mm/h, outperformed ConvLSTM, LSTM, FC-LSTM, and AlexNet, whose RMSE is 11.31, 11.50, 14.46, 15.88 mm/h respectively for rainfall prediction.

Plain Language Summary

Rainfall is not only related to current and previous meteorological conditions, but also to meteorological conditions of current location and surrounding regions. Existing short-term rainfall prediction methods mainly focus on radar echo extrapolation to predict the future radar echo maps, then retrival rainfall based on the predicted radar echo maps. These methods obtain rainfall through two separate steps usually lead to big accumulated errors. Therefore, Tiny-RainNet is proposed by combing convolutional neural networks (CNNs) with bi-directional long short-term memory (BiLSTM) to directly predict future rainfall based on sequential radar echo maps. Structure of Tiny-RainNet is simpler compared with existing rainfall prediction models combining CNNs with LSTM. In order to further reduce computation complexity of the Tiny-RainNet and obtain good rainfall prediction results, 10×10, not original 101×101, sequential radar maps are used as inputs of the Tiny-RainNet after making many tests with considering temporal-spatial meteorological conditions. The proposed model takes into account the influence of temporal-spatial meteorological conditions on rainfall prediction. This avoids the accumulated error caused by multi-step prediction methods. The overall performance of the Tiny-RainNet model outperforms the conventional rainfall prediction methods using CNNs and LSTM.

1 Introduction

Short-term rainfall prediction is important in meteorological services. It is the prediction of rainfall intensity within a relatively short time (generally 0–6 hours) for a specified area (Doviak, 2006). Present rainfall prediction methods mainly include numerical weather prediction (NWP) and radar echo extrapolation (Feng et al,. 2017). NWP uses mathematics, physics, atmospheric dynamics, and other methods to analyze weather evolution and to predict future weather. NWP products provide a basis for the daily predictions of meteorologists (Shu et al,. 2013; Pan et al,.2013). However, NWP has the shortcomings of uncertainty and parameterization error. These problems are mainly related to the degree of grid refinement and parameterization errors that mainly involve the initial value error and iteration errors in the calculations (Ma & Bao, 2017). Since NWP considers various complicated factors, the cost of rainfall prediction is greatly increased. NWP is more accurate for predictions covering a longer time period, and it has less ability to predict adjacent rainfall (Shi et al., 2015). Radar echo extrapolation technology can predict the future position and intensity of radar echoes, which can enable more rapid tracking prediction of strong convection systems (Zhang et al,. 2008; Otsuka et al,.2016). It is widely used in predicting rainfall. Research on the Real-time Optical flow by Variational methods for Echoes of Radar (ROVER) algorithm, proposed by the Hong Kong Observatory (HKO) (Woo & Wong, 2014), has been useful for accurate extrapolation of radar maps (Germann & Zawadzki, 2002; Sakaino, 2013). However, the accuracy of optical flow-based methods is limited because (1) the optical flow method only considers the correspondence between two adjacent frames and does not consider consecutive multiple frames; (2) the flow estimation step and the radar echo extrapolation step are separated, and it is difficult to determine the model parameters needed to produce accurate predictions.

Image detection, classification, regression, and other complex problems are being simplified by the use of big data sets and training models. Machine learning has helped solve many of the technical problems noted above. Artificial neural networks (ANN) have also been used for rainfall prediction. For example, Lee et al. (1998) predicted daily rainfall using a radial basis function (RBF) network based on location information. Because ANN easily falls into a local optimum, many samples are needed in training to achieve the best results. Therefore, more effective methods are being investigated to predict rainfall. A statistical machine learning method, support vector machine (SVM), has been widely used in radar quantitative rainfall prediction (QPF) because it is better at small sample prediction (Nikam & Gupta, 2013; Sehad et al., 2017; Yang et al., 2018). Additionally, the terrain-based weighted random forest method (Zhang et al., 2017) and other machine learning methods have been used for radar QPF (Sinclair & Pegram, 2005; Sideris et al., 2014; Guo, 2015; Verdin et al., 2016; Gou et al., 2018; Gou et al., 2019). Deep learning is a newer research direction in the field of machine learning, and it has been successfully applied to meteorological prediction. A new Dynamic Convolutional Layer for short-range weather prediction was presented by Klein et al. (2015). Qiu et al. (2017) proposed a multi-task convolutional neural network (CNN) model to automatically extract features from the time series measured at observation sites and leverage the correlation between the multiple sites for weather prediction via multi-tasking. Tang et al. (2018) predicted rainfall based on a geographical and temporal continuous conditional random field (GAT–CCRF) model to further reduce prediction error. However, both rainfall and radar echo maps are time series. The general machine learning method can only process spatial information, but it cannot process time information. Long short-term memory (LSTM) (Hochreiter & Schmidhuber, 1997) is an improved model of recurrent neural network (RNN) that can process information with a time dimension. The proposed LSTM may be able to improve the prediction accuracy of rainfall. However, with a large number of computing units, the network depth of LSTM is limited by the amount of computer memory.

Prediction of rainfall is a temporal–spatial sequence prediction problem. It inputs the past radar map sequence and outputs the future rainfall during a certain period of time. CNN and LSTM have recently been combined to predict rainfall, and good results have been achieved. For example, Shi et al. (Shi et al., 2015) integrated the convolution idea into LSTM and proposed the Convolutional LSTM (ConvLSTM) for rainfall nowcasting. ConvLSTM predicts the radar echo of 15 frames based on the radar echo of the past 5 frames and then calculates the rainfall using the Z–R relationship, where Z is the radar echo intensity in dB and R is the rainfall in mm/h. The results indicate that it is superior to the optical flow method. Zhang et al. (2018) combined CNN and LSTM to predict the radar echo map in the next 60 min based on the radar echo map sequence of 10 frames. In this study, we attempt to improve the network structure of the convolutional recurrent neural network (CRNN) and propose a Tiny-RainNet model, which combines CNN and LSTM. We used Doppler radar echo data from 2014 to 2015 in Shenzhen, China, to verify the proposed Tiny-RainNet model and to predict the rainfall during the next 1 to 2 hours.

2 Model

Tiny-RainNet, an end-to-end trainable neural network, improved the overall structure of the CRNN proposed by Shi et al. The network architecture of the Tiny-RainNet model is shown in Fig. 1.

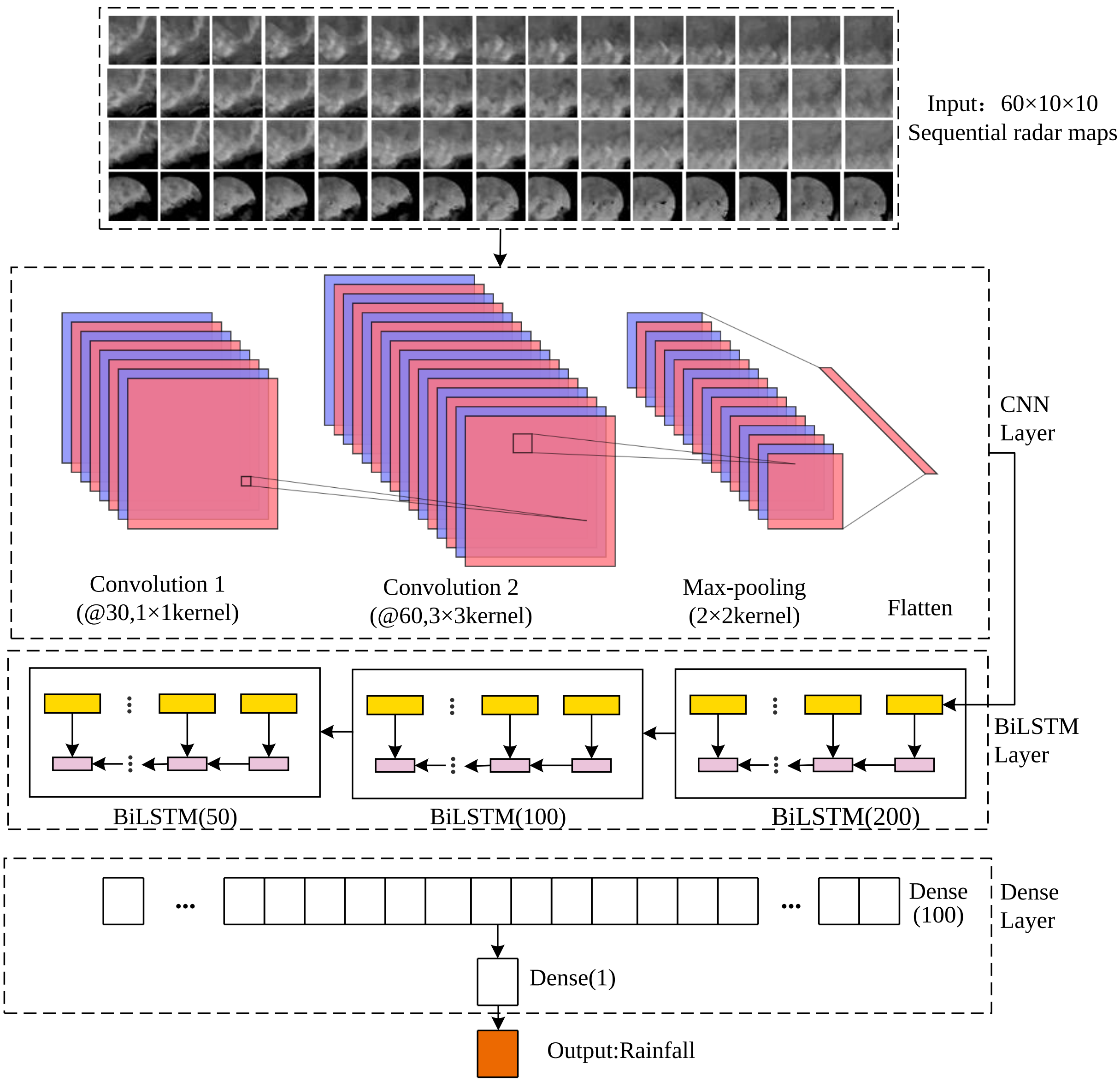


Fig. 1 Framework of the proposed Tiny-RainNet model architecture

It consists of three components, including the convolutional layer, the Bi-directional LSTM (BiLSTM) layers, and the dense layers. Table 1 lists the parameters of CRNN and Tiny-RainNet. The function of the convolution layer is to extract the context information from different receptive fields. BiLSTM is a combination of forward LSTM and backward LSTM, which capture the long-distance dependency and are well-suited for context-sensitive sequence annotation tasks. The output layer can be modified and applied to time series prediction problems. When using the radar map sequence for prediction, with limited information in the single radar map, the main information is stored in the time-series radar map. Tiny-RainNet inputs a series of gray radar maps. First, 2 convolutional layers are used to extract the characteristics of the cloud from radar maps, where conv1 (1×1 kernel) is used to fuse the features of radar maps between different time series, and conv2 (3×3 kernel) is used to extract the context information of the same radar map. Then, a dropout layer immediately after the convolution layer effectively prevents overfitting and produces a feature map with a height of 1. This feature map is sliced along the x-axis connects, and each slice is used as a time step for the BiLSTM network. Since the actual rainfall is related to the height and time span of the input radar echo maps, and the map information from different altitudes and times is correlated, Tiny-RainNet continuously uses 3 BiLSTM layers to increase the depth of the time series prediction and to reduce the error of rainfall prediction. Finally, the predicted rainfall is obtained by 2 dense layers. We used the Adaptive Gradient optimizer (Duchi et al., 2011) in the experiment. We saved the relatively better model configuration in Table 1, to be evaluated with a test set during the optimization process.

Table 1 Architecture comparison between CRNN and Tiny-RainNet

	Layer (type)	Configurations
CRNN	Input	W×32 gray-scale image
	Convolution	#maps: 64, k3×3
	Maxpooling	k2×2
	Convolution	#maps: 128, k3×3
	Maxpooling	k2×2
	Convolution	#maps: 256, k3×3
	Convolution	#maps: 256, k3×3
	Maxpooling	k2×2
	Convolution	#maps: 512, k3×3
	Convolution	#maps: 512, k3×3
	Maxpooling	k2×2
	Convolution	#maps: 512, k3×3
	Bi-LSTM	hidden units:256
	Bi-LSTM	hidden units:256
	Transcription	-
Tiny-RainNet	Input	60×10×10 gray-scale image
	Convolution	#maps: 30, k1×1
	Convolution	#maps: 60, k3×3
	Dropout	0.5
	Maxpooling	k2×2
	Bi-LSTM (Dropout(0.5))	hidden units:256
	Dropout	0.5
	Bi-LSTM (Dropout(0.5))	hidden units:128
	Dropout	0.5
	Bi-LSTM (Dropout(0.5))	hidden units:64
	Dropout	0.5
	Dense	100
	Dense	1

3 Data

3.1 Dataset

The dataset from the CIKM AnalytiCup 2017 in the Tianchi Big Data Algorithm Competition of Alibaba (https://tianchi.aliyun.com/competition/entrance/231596/introduction) includes gauge rainfall and Doppler radar echo maps of the target area. This information was collected by the meteorological observation center in Shenzhen, China, from 2014 to 2015. Each radar map covers a target location and its surrounding area and is marked as an X×Y mesh, where each grid point records the radar reflectivity factor Z. The dataset details are as follows:

1. Each radar map contains a target site (located at the center of the map). It covers an area of 101 km^2, depending on the latitude and longitude of the target location, whose area is marked as 101 × 101 cells.

2. Each radar map corresponds to the total amount of rainfall of the target site in the future 1 to 2 hours.

3. Radar maps with different time spans, with an interval of 6 min, a total of 15 time spans, represented by 'T': T0~T14; radar maps at different altitudes, with an interval of 1 km, from a distance of 0.5 km to 3.5 km, at 4 heights are represented by 'H': H0~H3.

The format of the data set is "id, label, radar_map." "Id" is the data sample number for a total of 10,000 samples; "label" is the rainfall of the target site; the radar_map is arranged in the "THYX" format.

In this paper, 80% Doppler radar maps and rainfall data from Shenzhen were randomly selected as training data, and the remaining 20% were used as test data to predict the total rainfall of the target location in the next 1 to 2 hours. We optimized the proposed Tiny-RainNet model as much as possible to minimize the prediction error.

The root mean square error (RMSE) is commonly used to reflect the total error of estimation results. The formula for calculating the RMSE is:

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}(R_a(i) - R_g(i))^2}, \tag{1}$$

where R_a is the gauge rainfall and R_g is the prediction rainfall.

3.2 Data Analysis

To analyze the distribution of target rainfall, Fig. 2 plots the histogram and box plot of the rainfall of 10,000 sample target sites in the dataset. More than 50% of the target sites had a rainfall of less than 10 mm/h; about 50% of the rainfall was evenly distributed from 10 mm to 60 mm, and the distribution density was larger at 20 mm to 30 mm. Then, the distribution density gradually decreased as the rainfall increased. About 1.5% of the rainfall values were distributed between 60 mm/h and 138.4 mm/h, which are referred to as outliers. The effect of outliers on rainfall prediction will be discussed in the Results section.

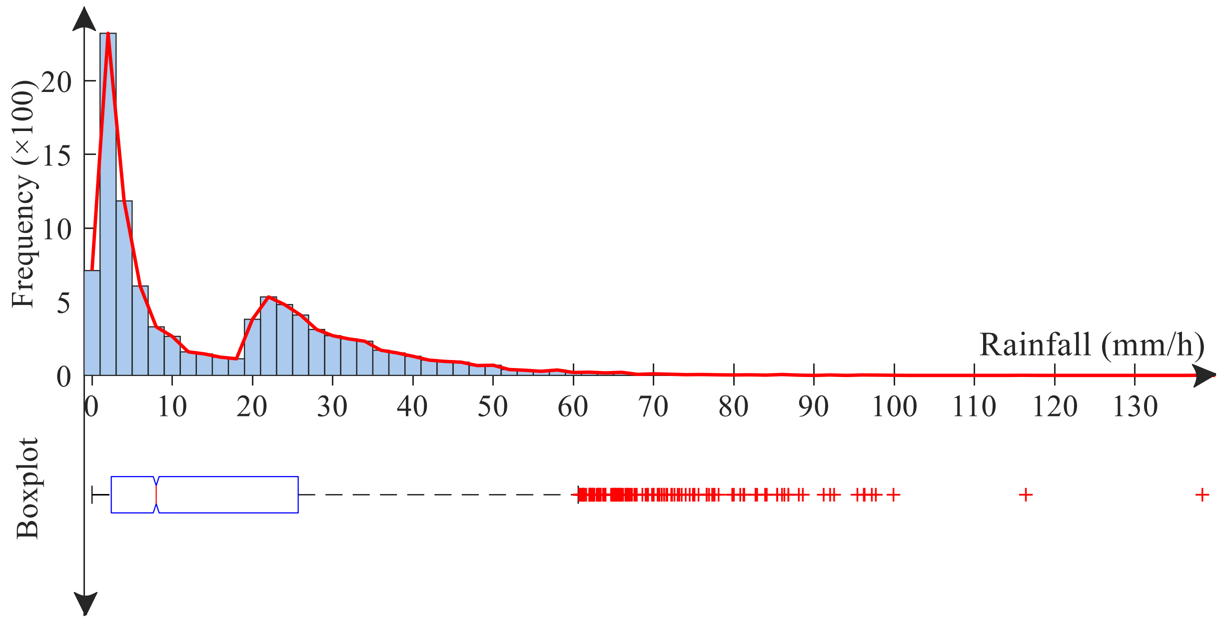


Fig. 2 Histogram and boxplot of rainfall

3.3 Pre-Processing for Data

Due to the magnitude of the original data set (15 × 4 × 101 × 101 = 612,060) and the large number of calculation units of BiLSTM itself, a large number of calculations are required if the original data is directly input into the proposed Tiny-RainNet model for rainfall prediction. Therefore, we needed to reduce the dimension of the original data. A direct method of dimension reduction is scaling the input radar maps. However, the map zooming process causes a loss of information. In order to minimize this loss, we first input radar maps with different degrees of scaling at the same time spans and different heights into the Tiny-RainNet model. After training and prediction, the RMSE of predicted rainfall and gauge rainfall was obtained. Then we obtained the RMSE of rainfall prediction results after radar image zooming of the same height and different time spans. Finally, according to the RMSE, we obtained the best scale of image scaling.

Rainfall is most relevant to the nearest meteorological conditions (He et al., 2017). Radar images of different sizes at T14 and H0~H3 were input into the Tiny-RainNet model, and the RMSE of rainfall prediction results was calculated (Fig. 3a). It can be seen that at any height of T14, the minimum RMSE corresponds to a 10 × 10 radar map. Especially at H1, precipitation prediction with a 10 × 10 radar map has the best performance.

Therefore, the radar maps of T0~T14 at H1 were scaled to the different size and input to the Tiny-RainNet model to train and predict precipitation. The RMSE of the predicted result was obtained and shown in Fig. 3b. Similarly, at the same height H1, regardless of time span, the minimum RMSE corresponded to a 10 × 10 radar map. In particular, the 10×10 radar map at T14 performed best. We conclude that scaling the original 101 × 101 radar map to 10 × 10 greatly reduces the required calculations but also helps to reduce the prediction error of the model.

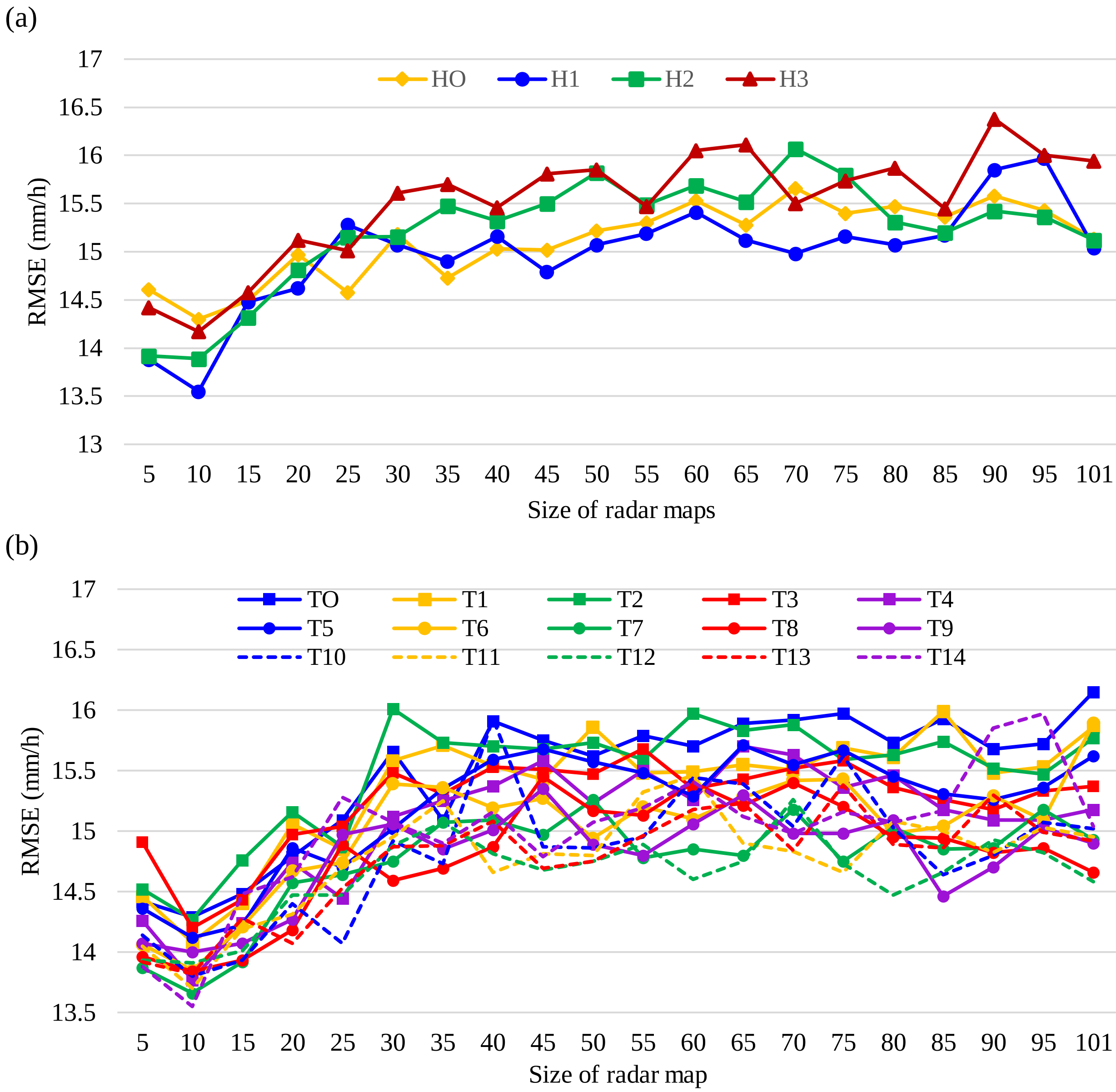


Fig. 3 RMSE curves of rainfall prediction using Tiny-RainNet model for Radar maps with (a) different sizes at H0~H3, T14 and (b) different sizes at T0~T14, H1

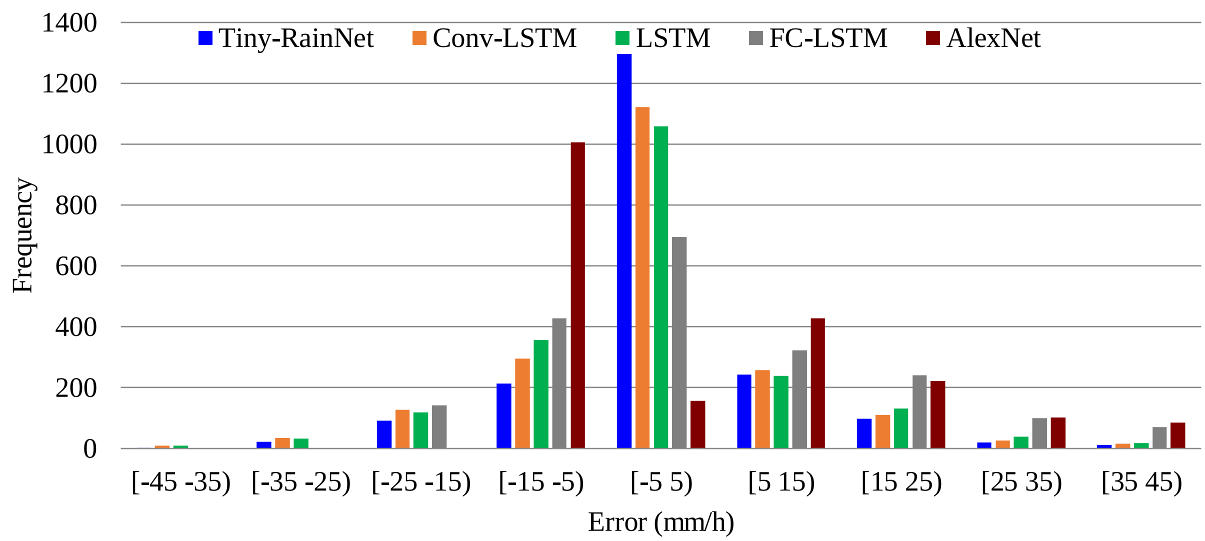
4 Experimental Results and Analysis

Using all values of radar echo map as features and the future precipitation of the target site as a label, the official data of the CIMK AnalytiCup 2017 competition was used to train linear regression (LR) for precipitation prediction. The RMSE was 14.69 mm/h. In addition, the RMSE of the top four models in this competition were 10.99 mm/h, 12.33 mm/h, 12.94 mm/h, and 13.2 mm/h, respectively (https://tianchi.aliyun.com/competition/entra nce/231596/rankingList). We trained the Tiny-RainNet model on the CIKM dataset, where the optimizer algorithm used Adam, the learning rate was set to 0.01, Batchisize was 1024, and the number of iterations was 6000. The RMSE of the Tiny-RainNet model is 9.67 mm / h, which is reduced by 34.17% compared to the LR method.

Conv-LSTM (Shi et al., 2015) , LSTM (Akbari et al., 2018), FC-LSTM (Kim et al., 2017), and AlexNet (Krizhevsky et al., 2012) were used for comparison to demonstrate the performance of the Tiny-RainNet model. To compare the prediction performance of the Tiny-RainNet model, all the tested models had similar parameters. The RMSEs of the four models are respectively 11.31,11.50,14.46, and 15.88 mm / h, which are reduced by 23%, 21.71%, 1.56% and -8.10% compared to the LR method. It is clear that the Tiny-RainNet model had better performance than Conv-LSTM, LSTM, FC-LSTM, and AlexNet. Fig. 4 is the error histogram of five methods used for precipitation prediction. It is the error distribution between predicted precipitation and gauge precipitation. The main error distribution interval between the predicted precipitation results and the actual results with AlexNet and FC-LSTM was [−15,15], and the overall error was large. This may be because the simple CNN is unsuitable for directly solving the problems of sequential input and small samples. However, the errors of LSTM, Conv-LSTM, and Tiny-RainNet were mainly between [−5,5], showing almost normal distributions and a relatively small overall error.

According to Section 2.2, there are 142 groups in the 10,000 groups of precipitation distributed between 60 mm/h and 138.4 mm/h. We assume that these outliers are caused by measurement errors or other abnormal conditions. During data preprocessing, this abnormal information was regarded as noise and discarded. Then we trained and tested the performance of Tiny-RainNet, Conv-LSTM, LSTM, FC-LSTM and AlexNet model using 80% and 20% of the total samples respectively. The RMSEs of the five models are 9.67,11.31,11.50, 14.46 and 15.88 mm / h and the prediction errors are more concentrated in the [−5,5] range, which is better than results of before discarding outliers.

(a)



(b)

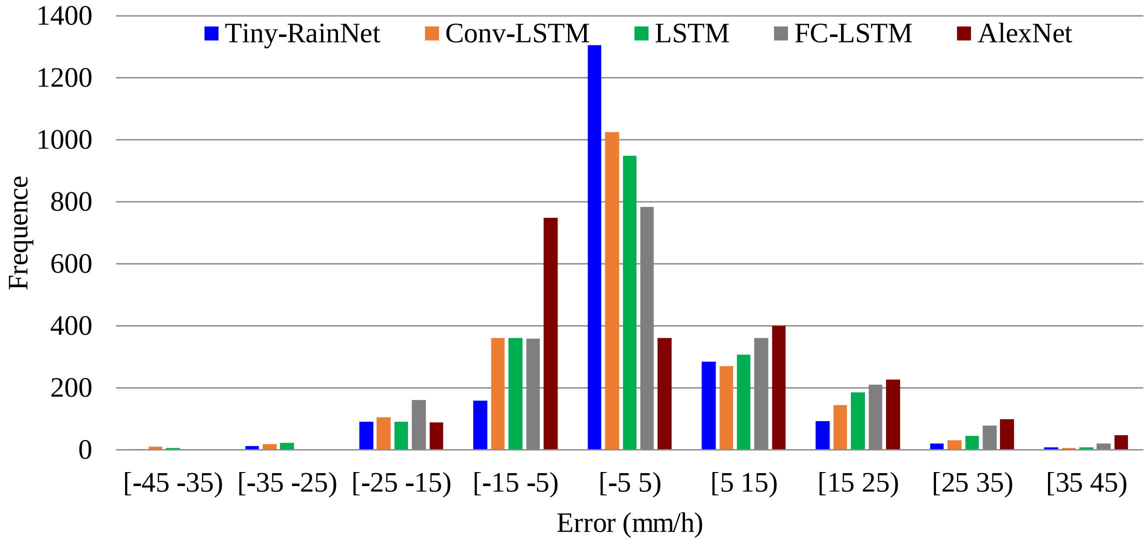


Fig. 4 Error histogram for precipitation prediction results of Conv-LSTM, LSTM, FC-LSTM, AlexNet, and Tiny-RainNet with data of (a) before discarding outliers (b) after discarding outliers

5 Conclusions

Precipitation prediction is a typical temporal–spatial and sequential prediction problem. According to the principle of precipitation formation, from the perspective of space, precipitation is related to the weather conditions of the current location and also highly susceptible to the surrounding environmental conditions. Precipitation is also closely related to the current weather as well as the weather of the previous period. We improved the network framework of CRNN and proposed a Tiny-RainNet model for short-term precipitation prediction. For the problem of precipitation prediction using complex sequential radar echoes, the proposed Tiny-RainNet model first extracts the context information of the radar echo maps through convolution layers, and then a BiLSTM layer is used to analyze and predict the context between the radar echo sequences. Adding a dropout layer after the convolution layer and BiLSTM layer effectively prevents the test result from being poorly fitted due to the training set being too rapid. The performance of the Tiny-RainNet model on the CIMK dataset proves that the network structure has advantages in the precipitation prediction problem based on spatial–temporal sequence.

(1) Optimal size of input radar maps of Tiny-RainNet is determined by combining temporal-spatial information.

(2) Compared to traditional precipitation prediction methods, including the optical flow method and NWP, the Tiny-RainNet model has a simpler structure and a faster calculation speed. It is more suitable for short-term precipitation prediction.

(3) The proposed Tiny-RainNet model combines the advantages of a convolution layer's ability to extract spatial information and BiLSTM's ability to deal with sequential problems. The comprehensive performance is better than that of existing similar models.

In the future, we will continue to improve the Tiny-RainNet model and apply it to mid-long term precipitation prediction.

Acknowledgments

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