Prediction of Rainfall in Rajasthan, India using Deep and Wide Neural Networks

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ABSTRACT

Rainfall is a natural process which is of utmost importance in various areas including water cycle, ground water recharging, disaster management and economic cycle. Accurate prediction of rainfall intensity is a challenging task and its exact prediction helps in every aspect. In this paper, we propose a deep and wide rainfall prediction model (DWRPM) and evaluate its effectiveness to predict rainfall in Indian state of Rajasthan using historical time-series data. For wide network, instead of using rainfall intensity values directly, we are using features obtained after applying a convolutional layer. For deep part, a multi-layer perceptron (MLP) is used. Information of geographical parameters (latitude and longitude) are included in a unique way. It gives the model a generalization ability, which helps a single model to make rainfall predictions in different geographical conditions. We compare our results with various deep-learning approaches like MLP, LSTM and CNN, which are observed to work well in sequence-based predictions. Experimental analysis and comparison shows the applicability of our proposed method for rainfall prediction in Rajasthan.

1. Introduction

Knowledge of rainfall characteristics plays an important role in understanding hydrology of a region as well as for efficient engineering, planning and management of water resources (Campiong et al., 2001; Halbe et al., 2013). It is one of the key natural resources that has a varying impact on human society (Le and Vo, 2020), such as, agricultural activities (Bhatt et al., 2013), hydro-power generation (Kumar et al., 2018), vegetation phenology (Chakraborty et al., 2018), flood control (Karunasagar et al., 2017; Sankaranarayanan et al., 2019), travel and maintenance activities, and sustainability of biodiversity (Pangaluru et al., 2015). This rainfall prediction further helps us in estimating the water requirement (Vaes et al., 2001) by the humans in a particular area or region. Developing countries like India have more advantage of accurate rainfall prediction, reason being, all the developed nations are either blessed with adequate rainfall or are equipped with advanced irrigation, water recycling, and harvesting facilities which ultimately makes them much more secured and fostered in terms of water consumption, recycling and harvesting.

In India, most of the rainfall is received during four months of monsoon season from June to September (Singh, 2017; Gadgil, 2003; Kumar et al., 2006). Rajasthan, a state in India comes under the arid zone (Goyal, 2004) and rainfall is the main source of overall water supply in the state. Rajasthan observes a varied climate range and had observed various floods (Mishra et al.) and droughts (Gadgil et al., 2005, 2002; Preethi et al., 2011) in past. With a lot amount of uncertainty in Meteorology (Curci et al., 2017), accurate prediction becomes a daunting task.

Prediction of occurrence and intensity of rainfall requires a lot of efforts right from data collection (Sapsford and Jupp, 1996; Weller and Romney, 1988), data cleansing (Hernández and Stolfo, 1998), data analysis (Agresti, 2003), data modelling (Benyon, 1996) and finally estimation and prediction with the help of a suitable model. There are countless parameters which derive the possibility of rainfall and its intensity over a region such as temperature of the air, distance of an area from ocean, amount of moisture contained by winds, distance from the mountain or mountain ranges, altitude of a land from sea level etc. We propose a data centric approach, where in place of receiving, recording and maintaining several parameters, we are using daily rainfall data of 71 years (from the year 1957 to
2017), obtained from rain-gauge stations installed in 33 districts of Rajasthan by Hydrology Department, Revenue Department and Indian Meteorological Department (IMD). This analysis on 71 years of data itself acts as a major contributor to the overall research and analysis we did.

In this work, we design and compare advance deep-learning models to identify patterns from the historical daily rainfall data of Rajasthan. For this purpose, we adapt and improve a wide and deep learning-based model, originally proposed by Cheng et al (Cheng et al, 2016) for recommender systems. We name our model as Deep Wide Rainfall Prediction Model (DWRPM) and evaluate its effectiveness in accurate rainfall prediction. The proposed model is compared with similar advance deep-learning-based models like multilayer perceptron, convolutional neural network and long-short-term-memory-based recurrent neural network.

The rest of the paper is arranged as follows. Section 2 reviews the related work. Section 3 explains the proposed Deep and wide rainfall prediction model (DWRPM). Details of experimental evaluations, model training and results of rainfall prediction are discussed in Section 4. Finally we conclude the paper in Section 5 and provide avenues for future research.

2. Related Work

Rainfall prediction methods are broadly classified into following four categories: empirical (Al Mamun et al., 2018), Awadallah et al. (2017), AlHassoun (2011), numerical (Ducrocq et al., 2002; Calvello et al., 2008), statistical (Li and Shao, 2010), Montanari and Grossi (2008), and machine learning (Cramer et al., 2017; Xingjian et al., 2015). Due to non-linear nature of Indian rainfall (Singh et al., 2012a), machine learning-based models are gaining more popularity over empirical, numerical and statistical methods for accurate prediction of rainfall events (Singh, 2017). With more focus on artificial intelligence and availability of high computational devices, these methods have gained a lot of attention in the field of prediction and estimation (Ko et al., 2020; Shah et al., 2018; Liu et al., 2019; Nayak et al., 2013; Darji et al., 2015). Recently, machine learning and deep learning-based approaches, such as support vector machine (SVM) (Ortiz-Garcia et al., 2014), artificial neural networks (ANN) (Acharya et al., 2013; Singh and Borah, 2013; Sahai et al., 2000), multilayer perceptron (MLP) (Esteves et al., 2019), recurrent neural networks (RNN) (Ni et al., 2020) and convolutional neural networks (CNN) (Zhang et al., 2020a) have become popular for predicting rainfall intensity. Some hybrid models have also been proposed for the purpose of rainfall prediction (Dabbi and Chaudhary, 2014).

Many researchers have proposed different ways to predict rainfall in Rajasthan (Dutta et al., 2013; Singh et al., 2012b), in India (Dubey, 2015a; Zhang et al., 2020b) as well as in abroad (Zaman, 2018; Kashiwao et al., 2017). There are methods that use multiple parameters for rainfall forecasting Zhang et al. (2020a); Pham et al. (2020), while some time-series-based methods use a single parameter (Sahai et al., 2000; Singh, 2017).

Zhang et al (Zhang et al., 2020a) designed a high-altitude combined rainfall forecasting model that uses convolutional neural network for rainfall prediction in next 12 hours in China. Authors have used data from 92 meteorology stations to test their model. Pham et al (Pham et al., 2020) have developed and compared several advanced artificial intelligence models namely adaptive network-based fuzzy inference system optimized with particle swarm optimization, artificial neural networks and, support vector machine for the prediction of daily rainfall in Hoa Binh province of Vietnam. Meteorological parameters used for this purpose are maximum temperature, minimum temperature, wind speed, relative humidity and solar radiation. Hernandez et al (Hernandez et al., 2016) proposed a deep learning approach combining an auto-encoder and a multilayer perceptron to predict the next day rainfall. The data was collected from a period of 2002 to 2013 from a meteorological station located in Manizales, Columbia. The parameters used in the experiments include temperature, relative humidity, barometric pressure, Sun brightness, wind speed and wind direction. (Hardwinarto et al., 2015) predicted the monthly rainfall over the region of East-Kalimantan, Indonesia using Artificial Neural Network. (Beheshti et al., 2016) used Centripetal accelerated particle swarm optimization (CAPSO) to predict the average monthly rainfall in the next five and ten years. Ni et al (Ni et al., 2020) developed two LSTM-based models for the streamflow and rainfall forecasting.

Gope et al (Gope et al., 2016) proposed a model to predict heavy rainfall events, 6 to 48 hours before the occurrence of rainfall in two cities of India, namely Mumbai and Kolkata. They used a stacked auto-encoder for feature learning and support vector machine and neural networks for classification of rainfall events above a certain threshold as heavy rainfall events. Dubey et al (Dubey, 2015b) used Artificial Neural Network for predicting rainfall in Pondicherry, India. Multiple parameters, such as, minimum temperature, maximum temperature, water vapor pressure, potential evapotranspiration and crop evapotranspiration were used for forecasting. For training and testing purposes only 800 and 200 samples respectively were used. A big-data centric approach using Artificial Neural Network on Map reduce framework was used by Namitha et al (Namitha et al., 2015) to predict daily rainfall prediction in India. The authors have used temperature and rainfall data of sixty three years provided by Indian Meteorology Department. Saha et al (Saha et al., 2020) used stacked encoder, ensemble regression tree and ensemble decision tree for the prediction of the Indian summer monsoon. Authors have identified new predictors for the purpose of monsoon rainfall forecasting. Samantaray et al (Samantaray et al., 2020) worked on prediction of monthly rainfall in Bolangir watershed of India. Authors designed and compared different machine learning algorithms like recurrent neural network, support vector machine and adaptive neuro fuzzy inference system. Pritpal Singh (Singh, 2017) has used historical time-series data to predict Indian summer monsoon rainfall. Author has mentioned that there is climatic variability and large fluctuations in monsoon rainfall in different parts of India. To handle these issues, the author has used the dataset prepared by Parthasarathy et al. (Parthasarathy et al., 1992, 1994) by taking the mean of all-India rainfall values by weighing each of the sub-divisional rainfall areas (306 well-distributed rain-gauges).
3. Deep & Wide Rainfall Prediction Model (DWRPM)

In this section, we first provide an overview of our approach, and then explain various steps in the subsequent subsections.

3.1. Overview

The main objective of this work is to adapt and improve the Wide and deep network for the prediction of daily rainfall using historical time-series data of Rajasthan, India. Time series-based prediction methods follow a concept that the current value in a time series always depends on previous time series values. Therefore, in this work, we use rainfall values of previous days to predict the current day’s rainfall. For instance, in order to predict the intensity of rainfall on October 9, 2020, the proposed work uses previous 210 days’ rainfall intensities, i.e. from March 12, 2020, to October 8, 2020. In this work, time-series data of daily rainfall of 33 districts of Rajasthan from 158 rain-gauge stations, installed by Hydrology Department, Rajasthan, Revenue Department, and Indian Meteorological Department (IMD) is analyzed over a period of 71 years (from the year 1957 to 2017). This analysis on 71 years of data itself acts as a major contributor to the overall research and analysis we did.

We are using a wide and deep neural network-based model, originally proposed by Cheng et al. (2016) for recommender systems. In our proposed work, the model is modified and improved for the prediction of the intensity of daily rainfall in the state of Rajasthan, India. The wide network is used to extract low-dimensional features, using a convolutional layer. High-dimensional features, on the other hand, are derived using Multi-layer perceptron (MLP) (Pal and Mitra, 1992) in which a sequence of rainfall intensity values are passed on to a deep network. In order to incorporate a generalization ability in the model, so that a single model can be used to make rainfall predictions in different geographical conditions, information of geographical parameters (latitude and longitude) is included while training the model. The operational steps involved in the development of our proposed DWRPM for the prediction of rainfall are shown in Figure 1. To evaluate the performance of the proposed method, we use two standard statistical metrics, namely mean absolute error (MAE) and root mean square error (RMSE). We compare our results with the advance deep learning models, widely used in time series analysis, like MLP, one dimensional convolutional neural networks (1-DCNN) and long short term memory (LSTM).

3.2. Dataset description and pre-processing

Rajasthan is the largest state of India and is situated on the North-Western part at 27.0238°N, 74.2179°E. For our experi-
ments, we have collected the daily rainfall data of 33 districts using more than 400 rain-gauge stations, over a period of 71 years (from the year 1957 to 2017). The dataset was noisy, reason being several rainfall intensity values were missing. In addition to this, some random characters were there instead of numerical values of rainfall intensity. Due to administrative reasons, there were changes in total number of districts in Rajasthan over this period of 71 years. There were some inconsistencies in the name of rain-gauge stations and their coordinates which made it difficult to identify rainfall values of a single station. After initial pre-processing and cleansing steps, we selected 158 stations for the purpose of our analysis. These selected rain-gauge stations are depicted on the map of Rajasthan as shown in Figure 2.

In order to provide an overview of the rainfall pattern in Rajasthan, an initial set of analysis of rainfall data obtained from the rain-gauge station situated at 27°49'N, 75°02'E in Sikar district of Rajasthan is presented in Table 1. We have shown rainfall statistics of three years, 1957, 1985 and 2017. It can be observed that about a significant portion of the annual rainfall occurs in the monsoon season from June to September and in the remaining days, there are a very few rainy day events. Daily rainfall generally varies from 0mm (no rain) to more than 500mm (in case of extremely heavy rainfall). Correct prediction of rainfall, therefore, is very important for proper management of water resources.

We have considered daily rainfall values of 210 days and geographical parameters like latitude and longitude to predict the intensity of next day’s rainfall. The daily rainfall intensity ranges from 0 mm to more than 500 mm while latitude and longitude ranges from 23°12’N to 29°55’N and 70°30’E to 77°35’E, respectively. Since the data is of different dimensions and dimensional units, therefore we normalize the data to make it dimensionally uniform. When the magnitude of different parameters in a dataset is different, the parameters with greater values often play a major role in model training than the parameters with lower values. To handle this issue, we use the most commonly used min-max normalization method to convert all rainfall intensity values to a number between 0 and 100 (latitude and longitude values are already in this range). The mathematical formula of the min-max normalization method is as follows:

\[ x^* = \frac{x - x_{\text{min}}}{x_{\text{max}} - x_{\text{min}}} \times 100 \]

where, \( x^* \) is the normalized value of the input sample, \( x \) represents a value in the original sample, \( x_{\text{max}} \) and \( x_{\text{min}} \) are the maximum and minimum values, respectively. Normalization can also help in improving the learning capability of the model and in reducing the computational complexity (Shanker et al. 1996).
3.3. Model description

In order to design a generalized model, which can predict rainfall in different geographical regions of Rajasthan we design an architecture inspired by wide & deep networks for the recommender systems (Cheng et al. [2016]) and extend it for time series based rainfall prediction. In what follows, we explain the main components of the proposed architecture.

3.3.1. The Wide Component: Convolutions

The wide component is used to memorize certain combinations of rainfall events, which is beyond the capabilities of the deep model. It is a generalized linear model of type $y = w^T x + b$. In the proposed model by Cheng et al (Cheng et al. [2016]), cross-product feature transformations were used as the wide component. In our proposed model the wide component is inspired by convolutional neural network (CNN) as shown in Figure 3. The basic components of a general CNN consists of 2 types of layers, namely convolutional layer and pooling layer (Gu et al. [2018]). The convolutional layer is composed of several convolutional kernels, which capture and learn the correlation of spatial features by computing different feature maps. The output of one dimensional convolutional layer with input size $N_i$ is:

$$a^{(l+1)}_k = b^{(l+1)}_k + \sum_{i=1}^{i=N_i} \text{conv1D}(w^{(l)}_{ik}, a^{(l)}_i)$$

where, $l$ is the layer number, $w^{(l)}_{ik}$ is the kernel from the $i^{th}$ neuron at layer $l-1$ to the $k^{th}$ neuron at layer $l$, $a^{(0)}$, $b^{(0)}$ activations, bias at $l^{th}$ layer.

Convolutional layer is followed by a pooling layer that is used to realize shift invariance by reducing the resolution of the feature maps. Van et al. [2020] demonstrated that 1D CNN works well in regression type of problems and can learn the correlation in and between the series very effectively. Therefore, instead of using raw features in the wide part of the network, we apply a convolutional layer to capture such combinations. In addition to this, to make our model more generalized with respect to different atmospheric conditions, we are using geographical parameters namely, longitude and latitude while designing and developing our model (details in Section 4.1.4 and Figure 3).

3.3.2. The Deep Component: Multilayer Perceptron

The deep component is a feed-forward neural network, specifically a multilayer perceptron, as shown in Figure 3. Sequence of daily rainfall intensity values are given as input, which are then fed into hidden layers of a neural network in the forward pass. Typically, each hidden layer computes:

$$a^{(l+1)} = f(w^{(l)}a^{(l)} + b^{(l)})$$

where, $l$ is the layer number and $f$ is the activation function, generally rectified linear units (ReLUs), $a^{(0)}$, $b^{(0)}$, and $w^{(0)}$ are the activations, bias and model weights at $l^{th}$ layer.

3.3.3. Joint training of the model

The model is trained using the joint training approach that optimises all parameters simultaneously by taking into account the output of the deep and wide components, geographical parameters and their weighted sum. It helps in providing an overall prediction, which is based on aforementioned components.

Table 1: Rainfall statistics of rain-gauge station situated at 27°49’N, 75°02’E in Sikar district of Rajasthan

| Year | Parameter                  | Jan | Feb | Mar | Apr | May | Jun | Jul | Aug | Sep | Oct | Nov | Dec |
|------|----------------------------|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| 1957 | Minimum Rainfall (mm)      | 0   | 0   | 0   | 0   | 0   | 0   | 0   | 0   | 0   | 0   | 0   | 0   |
|      | Maximum Rainfall (mm)      | 15.2| 0   | 0   | 0   | 55.9| 77.5| 50.8| 54.6| 64.8| 11.4| 0   | 0   |
|      | Average Rainfall (mm)      | 0.50| 0   | 0   | 0   | 1.80| 3.39| 4.45| 2.33| 2.54| 0.61| 0.61| 0.01|
| 1985 | Minimum Rainfall (mm)      | 0   | 0   | 0   | 0   | 0   | 0   | 0   | 0   | 0   | 0   | 0   | 0   |
|      | Maximum Rainfall (mm)      | 0   | 0   | 0   | 0   | 0   | 0   | 0   | 0   | 0   | 0   | 0   | 0   |
|      | Average Rainfall (mm)      | 0   | 0   | 0   | 0   | 0   | 0   | 0   | 0   | 0   | 0   | 0   | 0.23|
| 2017 | Minimum Rainfall (mm)      | 16  | 0   | 0   | 0   | 12  | 24  | 32  | 14  | 7   | 0   | 0   | 0   |
|      | Maximum Rainfall (mm)      | 0   | 0   | 0   | 0   | 0   | 0   | 0   | 0   | 0   | 0   | 0   | 0   |
|      | Average Rainfall (mm)      | 0.71| 0   | 0   | 0   | 0.52| 1.43| 2.68| 1.19| 0.33| 0   | 0   | 0.17|

Fig. 3: Selected architecture of DWRPM for rainfall forecasting. There are two major components: 1. The Deep component consists of mainly an input layer and 4 ReLU layers. 2. The wide component consists of a convolutional layer followed by a global average pooling layer. The information related to latitude and longitude is added separately.
also depicted in Figure 3

\[ y_{DWRPM} = w_{cn}h_{cn} + w_{co}h_{co} + w_{d}h_{d} \]

where, \( y_{DWRPM} \) is the prediction, \( h_{cn}, h_{co}, h_{d} \) are the output vectors of three sub-models namely wide-convolutional model, wide-coordinates model and deep model respectively, and \( w_{cn}, w_{co}, w_{d} \) are their respective weight vectors to be trained.

4. Experimental evaluations

4.1. Implementation details

The experimental program is coded using Keras (Chollet et al. [2015]) API of TensorFlow framework (Abadi et al., 2016; Gulli and Pal, 2017). The computer processor is Intel i7-8750H with 32GB RAM. Following paragraphs describe the important aspects related to the designing and implementation of the proposed method and the obtained results.

4.1.1. Selection of sequence length

As mentioned earlier, in time series-based prediction methods, previous times series values are used to make prediction of the next times series values. In our method, we use rainfall values of previous 210 days as input to make predictions for rainfall intensity of the next day. This number of days to be used as input, is one of the hyper-parameter and its value was chosen empirically by experimenting with different values, and its value was selected randomly in the range of 50 to 400. A possible reason why a sequence length of 210 gives the best result could be, though most of the rainfall in the state of Rajasthan is observed during four months of monsoon i.e., from June to September, still there are some rainfall events found to be occurring in the months of May, October and November as well. Other days have generally negligible rainfall intensities. There is a high probability of capturing this correlation well when a sequence length of 210 is considered, which is around seven months of frequent rain events.

4.1.2. Training, validation and test sets

Experimental dataset in this paper includes the rainfall data of 33 districts of Rajasthan from the year 1957 to 2017, collected from 158 rain-gauge stations installed by Hydrology Department of Rajasthan, Revenue Department and Indian Meteorological Department (IMD). We have used data from the year 1957 to 2006 for the purpose of training, data from the year 2007 to 2014 for validation and finally data from the year 2015 to 2017 for testing our model. This gives us 2858962 sequences for training, 429286 for validation and 140146 for testing. For creating a single generalized model for different atmospheric conditions, we include the geographical parameters (latitude and longitude) of these 158 rain-gauge stations while preparing the experimental datasets. Indian Meteorological Department (IMD) has divided rainfall intensity into seven categories:

1. no rain (0mm),
2. light rain (0.1mm to 7.5mm),
3. moderate rain (7.6mm to 35.5mm),
4. rather heavy rain (35.6mm to 64.4mm),
5. heavy rain (64.5mm to 124.4mm),
6. very heavy rain (124.5mm to 244.4mm) and
7. extremely heavy rain (244.5mm or more).

In our training set, we have 106452 samples of light rain, 110351 of moderate rain, 23133 of rather heavy rain, 9436 of heavy rain, 1894 of very heavy rain and only 154 samples of extremely heavy rain events.

4.1.3. Evaluation metrics

As shown by Glorot and Bengio (2010) and He et al. (2015a), to evaluate the overall accuracy of predictions, we use root mean square error (RMSE) and mean absolute error (MAE) as the basic evaluation metrics.

\[
\text{RMS}E = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (y_i - \bar{y}_i)^2}
\]

\[
\text{MAE} = \frac{1}{N} \sum_{i=1}^{N} |y_i - \bar{y}_i|
\]

where, \( N \) represents the number of samples, \( y_i \) is the actual rainfall of the \( i \)th sample and \( \bar{y}_i \) is the corresponding prediction.

4.1.4. Model Training

We made a parameter exploration concerning the batch size, hidden layers, number of neurons, dropout rates and optimization algorithms using trial-and-error method. The network configuration of DWRPM used in our experiments is shown in Figure 3. The deep part is a Multi-layer perceptron with an input layer; 4 hidden layers containing 300, 200, 100 and 50 neural units with ReLU as the activation function; and finally a dense output layer. In order to prevent over-fitting of the model, dropout layers (Srivastava et al., 2014) with dropout rate 0.3 are added after each hidden layer. The wide part contains a convolutional layer with 100 filters, each of size 1x5, followed by a global average pooling layer. The output of both the wide and deep networks is concatenated, along with the latitude and longitude values, and the model is trained using the joint-training approach, explained in Section 3.3.3. We use Adam optimizer (Kingma and Ba, 2015) for training with Mean Square Error (MSE) as loss function. It is calculated as follows:

\[
\text{MSE} = \frac{1}{N} \sum_{i=1}^{N} (y_i - \bar{y}_i)^2
\]

where, \( N \) represents the number of samples, \( y_i \) is the actual rainfall of the \( i \)th sample and \( \bar{y}_i \) is the corresponding prediction. The goal of the model is to find optimized parameters that minimizes MSE

\[
\min_{\theta} \text{MSE}(\theta)
\]

where, \( \theta \) is the total number of trainable parameters. Weights of the network are initialized using HE initialization (He et al., 2015b). Model is trained for 100 epochs with batch size equals to 8.
4.1.5. Baseline approaches

To establish the efficiency of the proposed work, we compare it with a few deep-learning-based approaches. These approaches are observed to work considerably well for sequence-based prediction methods (refer Section 2). We use the same set of input data, obtained after pre-processing, for our proposed approach and for all the baseline approaches. This is done to avoid discrepancies emerging from different sets of input data. The network architecture of the baseline approaches, which is selected (after experimenting with various hyper-parameters) for the comparative analysis with the proposed method is explained in the subsequent paragraphs. In all these approaches, we use Adam optimizer for training and MSE as loss function. Input sequence length is 210. Besides this, we concatenate the latitudinal and longitudinal values separately, so that the sequence of rainfall intensity values can be learned efficiently and overall learning process gets enhanced (Figure 4).

**Long Short-term Memory (LSTM):** The network architecture for LSTM is shown in Figure 4a. We found that this sequence network works well with two LSTM cells, each of size 50. The output of the second LSTM layer is combined with coordinate values, which is finally provided to an output layer for predicting the value of rainfall intensity. Here as well, to prevent the over-fitting, we use an intermediate dropout layer at the rate of 0.3.

**Multilayer perceptron (MLP):** The network architecture for MLP is shown in Figure 4b. It contains an input layer and 3 hidden ReLU layers with 300, 200 and 100 neural units respectively. The output of the last hidden layer is concatenated with latitude and longitude values and fed into the dense layer. Dropout layers at rate 0.3 are added after each hidden layer, as a regularization method to prevent over-fitting.

**Convolutional Neural Network (CNN):** The network architecture selected for CNN is given in Figure 4c. It has two convolutional layers with 100 filters of size 1x5 each, followed by a max pooling layer, convolutional layer and a global average pooling layer. Coordinate values are appended with the output of global average pooling layer, which is finally given to the output layer for prediction. Dropout method is used as a regularization technique to handle over-fitting. The dropout rate is chosen as 0.2.

4.2. Results and discussion

In the following subsections, we present the results of experimental analysis and comparison of the proposed method with the baseline approaches described in Section 4.1.5.

4.2.1. Forecasting accuracy of DWRPM

Before testing the proposed model for rainfall forecasting in 158 rain-gauge stations, we need to check its stability and feasibility. For this purpose, we take rain-gauge station situated at degrees as an example to check the efficiency of model in prediction of rainfall. Figure 5a shows its prediction results from the year 2016-2017. Once the model is stabilized for this rain-gauge station, by tuning various hyper-parameters (details of hyper-parameters and model training are given in Section 4.1.4), it is used for prediction of daily rainfall intensity values for all 158 stations. Out of total 140146 samples of test dataset, observed between the year 2015-2017, proposed model is found to be more accurate in the prediction of light rainfall and moderate rainfall events (0.1mm-35.5mm). However, the accuracy of the model is comparatively lesser for very heavy rainfall events. The main reason is that the number of heavy rainfall events are significantly lower than the light and moderate rainfall events (refer Section 4.1.2). In addition to this, we are only using the rainfall intensity values as a major parameter for prediction, therefore it is difficult to learn such characteristics of rainfall. Besides this, too less rainfall may not activate neurons.

4.2.2. Generalization ability of DWRPM

Atmospherically, Rajasthan is divided into four zones, namely: North West Desert Region, Central Aravalli Hill Re-
Fig. 5: Prediction results of DWRPM for four rain-gauge stations, each picked from a different atmospheric zone (Section 4.2.2). Results are from year 2016 to 2017. (a) Prediction results of rain-gauge station situated at 29°12’N, 73°14’E in North-West desert region, (b) Prediction results of rain-gauge station situated at 26°04’N, 74°46’E in Central Aravalli hill region, (c) Prediction results of rain-gauge station situated at 26°41’N, 75°14’E in Eastern plains region, and (d) Prediction results of rain-gauge station situated at 25°18’N, 75°57’E in South-Eastern plateau region.

Table 2: Zone-wise prediction results

| Zone Name                  | MAE   | RMSE  |
|----------------------------|-------|-------|
| North-West                 | 0.679 | 1.512 |
| Central Aravalli Hill Region | 0.821 | 2.43  |
| Eastern Plains             | 0.748 | 1.634 |
| South-Eastern Plateau Region | 0.903 | 2.613 |
| Rajasthan Region           | 0.776 | 2.171 |

4.2.3. Comparison with baseline approaches

To establish the significance of present work, we compare the results of our model with the baseline approaches. Figure 6 shows prediction results of DWRPM and other approaches on a rain-gauge station situated at 29°32’N, 73°27’E for six months, from May to November, of the year 2017. Overall comparison of our model and other three approaches in rainfall prediction on all 158 rain-gauge stations from the year 2015 to 2017 is presented in Table 4. It shows that the RMSE and MAE values of the proposed DWRPM is minimum and it gives better prediction results than the other advanced deep-learning methods, which are generally used for sequence-based predictions. The main reason for the better performance of DWRPM is that it...
Table 3: Prediction results of four rain-gauge stations, one from each atmospheric zone

| Zone Name                  | District Name | Station Name | Latitude | Longitude | MAE  | RMSE |
|----------------------------|---------------|--------------|----------|-----------|------|------|
| North-West Desert          | Ganganagar    | Anupgarh     | 29°12'N  | 73°14'E  | 0.43 | 0.60 |
| Central Aravalli Hill Region | Ajmer        | Bhinai      | 26°04'N  | 74°46'E  | 0.62 | 1.12 |
| Eastern Plains             | Jaipur       | Dudu         | 26°41'N  | 75°14'E  | 0.55 | 1.18 |
| South-Eastern Plateau Region | Bundi      | Patan        | 25°18'N  | 75°57'E  | 0.67 | 1.59 |

Fig. 6: Comparison of DWRPM and three deep-learning approaches. Here we show prediction results of all the models on a rain-gauge station situated at 29°32'N, 73°27'E from May to November, of the year 2017. (a) Prediction results of MLP, (b) Prediction results of LSTM, (c) Prediction results of one dimensional CNN and, (d) Prediction results of the proposed DWRPM.

uses the generalization ability of MLP and also captures correlation in daily rainfall values using convolutions, which is an important component of CNN. This establishes the usefulness of the proposed method in prediction of rainfall in the Indian state of Rajasthan.

Table 4: Comparison of the proposed DWRPM with other deep learning methods, widely used for sequence-based prediction

| Method | MAE   | RMSE  |
|--------|-------|-------|
| MLP    | 1.3137| 2.7808|
| 1-DCNN | 0.8406| 2.2894|
| LSTM   | 0.8750| 2.3095|
| DWRPM  | 0.7765| 2.1716|

5. Conclusion and Future Work

This paper has developed and presented a deep and wide network-based approach for the purpose of daily rainfall prediction in the Indian state of Rajasthan. Daily rainfall data of 71 years, from the year 1957 to 2017, has been used in designing and validation of the proposed deep and wide rainfall prediction model. The results are promising and the model has generalization ability. Same model works well for forecasting rainfall in different atmospheric zones of Rajasthan. A comparison with the advance deep-learned-based models like MLP, LSTM and 1-DCNN is also presented. The experimental analysis and comparison exhibits the importance of the proposed model for rainfall forecasting. While the model works well in prediction of light and moderate rainfall events, scope for improvement is there in prediction of heavy and very heavy rainfall events. Future work includes a comprehensive analysis of the applicability of the proposed model in different states of India. We shall also include more number of parameters and explore the ways to increase the forecasting accuracy for heavy and very heavy rainfall events. We also plan to estimate and predict the rainfall for longer duration of time.
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