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Improving Rainfall Forecasting via Radial Basis Function and Deep Convolutional Neural Networks Integration

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Abstract: The foremost challenge of rainfall forecasting is the intensity of rainfall in some particular stations. The unpredictable rainfall volume owing to the climate transformation can root cause for either overflow or dryness in the reservoir. In this article, we coin a novel model to predict the monthly rainfall by using an Ensemble Radial basis function Network and a One-Dimensional Deep Convolutional Neural Network algorithm. In the first step, nine climatological parameters, which are highly related to monthly rainfall disparity, are given as input for an ensemble model. In the second step, a hybrid approach is proposed and compared with Bayesian Linear Regression (BLR) and Decision Forest Regression (DFR). Experimental results show that the ensemble approach yields good results in seizing the multifaceted association among causal variables and also it extracted the most relevant hidden features of hydro meteorological rainfall system.

Keywords: Deep Convolutional Neural network; Rainfall; Prediction; Meteorology.

Introduction

Accurate prediction of precipitation is quite ambiguous, very difficult job owing to the complication of meteorological conditions and the depiction of the mathematical model is also quite difficult because it is purely a non-linear model. Weather forecasting makes positive the sustainable development of the economy in the society. The interest in forecasting precipitation history started in the 650 B.C., when the observation of clouds was used as a pattern by the famous Babylonians. Later, various forecasting theories were proposed but the results were not satisfactory and also it needs to understand the weather and hence instruments such as radiosonde telegraphy were invented to record the weather. Surprisingly, mathematical equations were derived and solved for weather forecasting. In the last few decades, researchers have identified that the distribution of spatial and temporal rainfall is an impact of climatic changes and the availability of water on the earth's surface. It greatly influences on agricultural activities and it is directly proportional to the crop production. Hence the distribution of rainfall prediction plays a major factor in crop production, agricultural planning, drought, flood, etc. For example, in India, intense precipitation has been recorded in recent years such as Gujarat–Maharashtra in the year of 2005, Uttarakhand in the year of 2013, South Tamil Nadu in the year of 2015, and Kerala in the year of 2018 this leads to remarkable loss in both human life and

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property. Anyhow the precise expectation of cyclical rainfall forecasting becomes more plausible amongst rainfall researchers around the world. However, the variability of intrinsic spatial and temporary rainfall prediction is the most challenging variable to forecast. Because of the cases, temporal and spatial measures have not been directly determined by numerical methods and the results yielded by these methods are also not. But an interesting fact about spatial and temporal rainfall prediction is it comes under the rainfall disaggregation problem. Rainfall prediction problems can be categorised into (i) rainfall aggregation – which finds the areal rainfall with the help of familiar approaches such as Thiessen polygon method, isohyetal method, kriging method, spline method, etc. and (ii) rainfall disaggregation – this involves disaggregating daily, hourly, monthly or converging lengthier rainfall period into shorter, exhibiting rainfall with the help of Combining Neural Computation and Wavelet Technique.

In recent years, with the help of neural networks rainfall forecasting has made it easier for researchers to investigate that. This neural network-based prediction method has become more appreciated for nonlinear demonstrating such as follows: (i) stream flow prediction run of urmia (ii) rainfall runoff prediction (iii) sea level forecasting (iv) water level variations, (v) rainfall forecasting. In order to evaluate the outcome of these models Neural Network could be the exact and most accurate model to simulate and forecast.

In the proposed work, we presented the hybrid deep learning (Hemalatha et al., 2023) based approach to forecast monthly rainfall prediction in India. The proposed results were related to top resulted rainfall forecasting methods. The experimental observations show that the projected hybrid model yields better results predicting rainfall months in high annual averages comparatively other methods. This proposed work aims to extract useful evidence among rainfall (target) and its connected meteorological causal variables to progress a multistep ahead rainfall predication in a monthly manner.

Literature Survey

In Bangkok, the experiment was conducted by Hung et al. (2009) (in Urmia lake) by comparing the feed forward neural network with a light obstinate model for 75 rain gauge stations. Their results have shown that the Feedforward neural network using hyperbolic tangent transfer function produced accurate rainfall generalisation. In the country of Greece (Hemalatha et al., 2020), four meteorological stations were chosen to predict the monthly mean and cumulative rainfall within a historical of the last four months. They demonstrated and determined that the results of the neural network were very accurate in rainfall forecasting.

In Japan, Kashiwao et al. (2017) proposed a rainfall prediction method for local locations in the regions of their country. The daily data has been extracted from the Japan Meteorological Agency. In particular, Japan has four seasonal ranges from subarctic in the northern region to subtropical in the southern region but the conditions will vary from among Pacific towards the Japan Sea. Based on this information the authors have done the investigations and experimentations. They implemented a hybrid algorithm by ensembling (a) random, optimisations (b) neural networks and (c) radial basis function networks in the build least square method. During their experimentation, they found that the artificial neural network showed superior results when compared with the Hung et al. (2009) method.

In-order to develop the application for multistep rainfall forecasting, Nourani et al. (2019) proposed the Emotional Artificial Neural Network method. In addition to predicting the long-term rainfall forecasting, authors such as Nourani et al. (2019) and Ali et al. (2020) have developed the threshold-based hybrid method and the data intelligence-based method.

Vikas Kumar et al. (2022) proposed the rainfall prediction method by using parameters such as date, location, extreme temperature, least temperature, moisture, wind direction, and evaporation. All the above parameters were trained using logistic regression, K-nearest neighbour, decision tree and random forest. They found that among the four algorithms K- Nearest Neighbour and Random Forest (Hemalatha et al., 2020) gave 88% accuracy.

Irrespective of the applications, Deep neural network yields the better results. Deep neural network consists of many number of hidden layers and many non-linear levels to do the operations successfully. Training such the deep architecture will be similar to training the deep learning framework. When a deep framework is comprised of more than two hidden in-between layers the higher layers such the third, fourth fifth layers constitute abstractions on the uppermost next aforementioned hidden layers. Deep Neural Networks have an excellent feature, as it can be possible to extract the high-level feature abstractions from the given input of data by processing the input into multiple hidden layers with combinations of linear and non-linear levels.

To summarise the literature art, a dense and plenty of rainfall forecasting methods (Gupta et al., 2015;

Geetha et al., 2011; Abhishek et al., 2012) have developed with the help and combination of computing advancements and drastic public availability of weather data which leads to accurately predict the rainfall. On the other hand deep learning-based model gives the most accurate results in forecasting rainfall and it is an excellent combination of both deep learning and rainfall prediction. Though many successive state-of-the-art models have given accurate rainfall forecasting still there is a long gap and challenges in hydrological research and climate assessment. This proposed work is a great attempt to find the monthly rainfall prediction using a deep NN framework.

Main Contribution of this Research

The foremost impact of the research paper is we propose a hybrid model to predict the multi-step ahead daily rainfall with a more accurate temporal basis. In addition, this model will be extended to multi-step ahead rainfall prediction. In order to progress the accuracy of the prediction in our proposed work we provided the ensemble method by combining a radial basis function network and one-dimensional convolutional neural network. A comparative study is performed by relating the performance metrics with high results given models.

Proposed Work

Convolutional Neural Network

A convolutional neural netwok consists of many neurons interconnected with each other. Each interconnected neuron contains weight and bias. The weight and bias can be adjusted to improve the output. Each neuron will be fed by some input and processed by performing a dot product with non-linearity, the resultant output will be fed to the following succeeded neurons. The final output of the entire network will be a single differentiable counting function. Convolution is a perception of digital signal processing where signals are handled in a time series manner. In a deep network also convolution process takes place by stacking matrix multiply layers. Basically in the architecture of a convolutional neural network, many layers are stacked on the uppermost of each layer called Convolutional layer – an integration of two functions given in Equation (1), pooling and fully connected layer.

$$Sig(t) = \int (a)w(t-a)da \tag{1}$$

The Convolution process is given in equation (2) (Narejo et al., 2020)

$$Sig(t) = (x \times w)(t) \tag{2}$$

For performing the convolution, two variables named as x, w are given as input and kernel. The feature map will be provided as output and it is referred as $Sig(t)$. Irrespective of the application when we apply data to the CNN, it will be given as a multidimensional array and its parameters will be given as kernel functions. The immediate layers are called as pooling layer and finally, output will be taken from the fully connected layers. When we see the overall architecture of a convolutional neural network, from the given input data, the features will be automatically learned and training will be done with the features it learns. During training, the network will change the entire kernel matrix on each iteration. The single-dimensional deep convolution neural network training procedure (Haidar and Verma, 2018) as given below.

Algorithm 1:Training the CNN

Input: Dataset to be trained, dataset to be validated
Output: Trained CNN

Step 1: Set the weights and bias of the network
Step 2: For each epoch do:

(i) Input the data for training.
(ii) Equate the actual values to predicted values of rainfall

Step 3: Calculate the cross-entropy loss function $L = -1\text{n}(p_c)$ where p_c is the predicted probability for the correct class.
Calculate the input to the softmax layer backward phase, $\dfrac{\partial L}{\partial \text{out}_s(i)} = \begin{cases} 0 \text{ if } i \neq c \\ -\dfrac{1}{p_i} \text{ if } i = c \end{cases}$ where c is correct class.

Step 4: Back propagate the error and fine-tune weights.
Step 5: Find the results of testing data.

Radial Basis Function Network (RBFN)

A radial Basis Function Network is a non-linear network with an employee's radial basis function and activation function. The resultant output will be the linear combination of radial basis function and neural parameter. Basically, it has three layers (i) the input layer and (ii) the hidden layer comprised of the non-linear radial basis function activation function and the output layer. The given input will be needed in the form of vector $x \in \mathbb{R}^n$. The final output of the network will be a scalar function and it is represented as $\mho = \mathbb{R}^n \rightarrow \mathbb{R}$, and it is given as

$$\mho(x) = \sum_{i=1}^{N} a_i \rho(\|x - c_i\|) \quad (3)$$

where N is the various neuron numbers in the middle layer and c_i is the neuron vector i, a_i is the neuron weight.

Proposed Ensemble Rainfall Predictor

The proposed method is a hybrid method where the radial basis function network and one-dimensional deep convolutional neural network are ensembles for refining the accuracy of rainfall prediction. The anticipated architecture is shown in Figure 2. For one dimensional deep convolutional neural network the filter size used is 32 and the kernel size used is 3. The activation function chosen are Relu function. The Max pooling size used is 2. The convolutional layer is the main block of CNN. The layers are entirely associated and neurons in the upcoming layer are associated with the preceding level neurons. In order to enhance the rainfall, predictors, neurons connected with local regions were employed

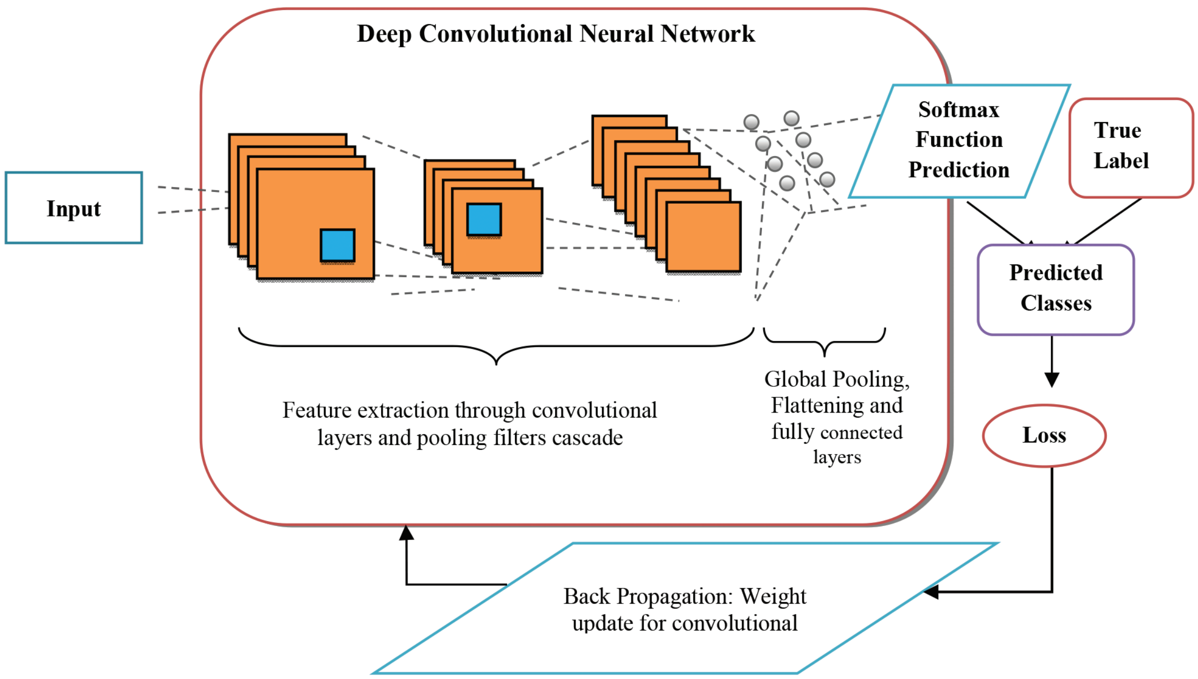

Figure 1: A schematic representation of deep CNN.

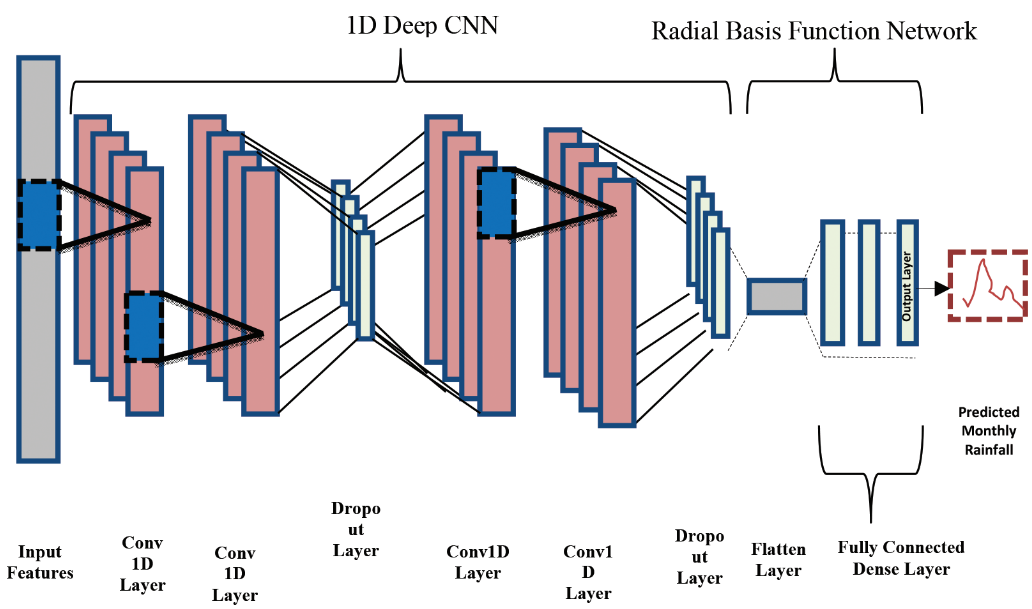

Figure 2: Proposed block diagram architecture.

in the proposed work. In the proposed ensemble CNN shown in Figure 1 is employed as a stack of layers. Depending on the filter used the usage of the stacked layer is done. In specific going deeper into the layers finely enriches the learning off given features. For the rainfall features $x = x^1, x^2, x^3, x^4 \ldots x^n$ whereas n is the rainfall parameters to be given as input and it is finely trained by the ensemble algorithm. The hybrid algorithm as is follows:

Algorithm 2: Hybrid Algorithm

Step 1: Initialise step as

(i) $a = 0$,

(ii) $b = 0$ and

(iii) w_{ij}, w_{ik} as random generation

Step 2: Set $a = a + 1$ and parallel update the weights of w_{ij}, w_{ik}.

Calculate the error function $E_a(w)$.

Step 3: Initialise $b = b + 1$.

Step 4: Set $a = a + 1$ and calculate w_{ij}, w_{ik}

The proposed approach anticipates predicting the ensemble performance in a rainfall prediction work. The proposed ensemble predictor maps the rainfall parameters to $rn \rightarrow$ R:

$$\left\{\begin{matrix} \partial_1^1\partial_2^2\partial_1^3\ldots\ldots\partial_1^n \\ \partial_2^1\partial_2^2\partial_2^3\ldots\ldots\partial_2^4 \\ \partial_3^1\partial_4^2\partial_3^3\ldots\ldots\partial_3^4 \\ \partial_4^1\partial_4^2\partial_4^3\ldots\ldots\partial_4^4 \\ . \\ . \\ . \\ \partial_n^1\partial_n^2\partial_n^3\ldots\ldots\partial_n^4 \end{matrix}\right\} ® \left\{\begin{matrix} r_1 \\ r_2 \\ r_3 \\ r_4 \\ . \\ . \\ . \\ rn \end{matrix}\right\} \tag{4}$$

where ∂_j^i represents the input parameters of rainfall and rn is the rainfall values. Rainfall inconsistency is exaggerated by several atmospheric circumstances. These circumstances encompass local and global dissimilarities in the atmosphere which result in rainfalls in a certain locality. Such conditions are strictly measured and it is called as rainfall parameters. The parameters are greatly influenced and they affect the rainfall at specific times of the year.

Experimental Results and Discussion

Five cities in the Indian country have chosen such as Chennai, Gujarat, Madurai, Andhra Pradesh, and Navi Mumbai. The reason for choosing the various location are the climatic conditions vary from area to area. The regions with less rainfall amount are under relentless danger of droughts, while more rainfall regions result in heavy floods (Pichuka et al., 2017) and landslides. The period from 1992 to 2017 showed nine closely connected meteorological parameters (Khan et al., 2020), which are chosen and extracted such as maximum air temperature, geopotential height, longwave radiation, maximum relative humidity, minimum relative humidity, u-wind speed,v-wind speed, sea level pressure and rainfall are extracted. The above said values are acquired from the Indian Meteorological Department with a spatial resolution of 0.25° (latitude) × 0.25° (longitude)

The experimentation was performed on Python Development. In order to attain the value of all casual and targeted variables inverse distance weighting method (Khan et al., 2020) is employed. The parameters are finely scaled with the help of Maxscalar in Python. Later the datasets were trained and tested using the ensemble rainfall predictor using k-fold cross validation.

Performance metrics for the proposed Ensemble Radial basis function Network and One-Dimensional Deep Convolutional Neural Network and the other two models Decision Forest Regression and Bayesian Linear Regression are presented for comparison and it is given in Table 1. It is noticed that for Bayesian Linear Regression the average Root Mean Square Value ranges from 6.25 to 8.9, for Decision Forest Regression the average Root Mean Square Value ranges from 6.64 to 9.41 and for the Proposed hybrid approach the average Root Mean Square Value ranges from 6.25 to 8.23. From the results, it is found that the Proposed Ensemble approach had lesser Root Mean Square Value while training and testing across various cities and it provided better results. Normalised Square Error ranges from 0.18 to 0.24. The range of averaging the r value is from -0.2342 to 0.9999. From the observation, it is observed that the performance of the Ensemble classifier is enhanced than further two models – Decision Forest Regression and Bayesian Linear Regression while checking for NSE. The period from 1992 to 2017 the rainfall and runoff value is given in Figure 3.

Conclusion and Future Work

The proposed work presents daily rainfall time series prediction in India using an ensemble radial basis function network and a one-dimensional deep convolutional neural network. While surveying the

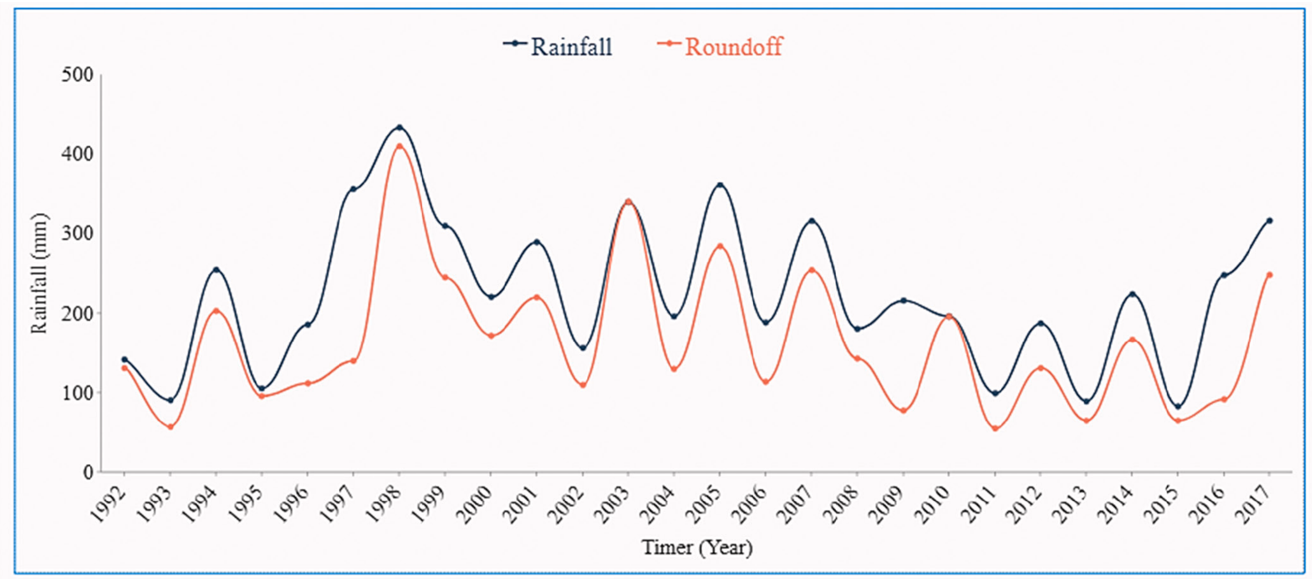

Figure 3: Rainfall variations for the year 1992 to 2017.

Table 1: Performance statistics of RMSE and NSE at different locations in India

City	*Bayesian Linear Regression (BLR)*		*Decision Forest Regression*		*Proposed Ensemble approach*	
	Training	*Testing*	*Training*	*Testing*	*Training*	*Testing*
Chennai	0.094573	0.632326	0.48527	0.45792	0.43532	0.87657
	7.89	7.85	6.64	6.67	7.46	7.41
	0.19	0.17	0.18	0.19	0.18	0.18
Gujarat	0.627539	0.367674	0.99990	0.219738	0.97652	-0.2342
	6.25	6.43	6.78	7.2	6.25	6.66
	-0.03	-0.04	0.3	0.4	0.25	0.25
Madurai	0.627539	0.7623	0.87654	0.24869	0.9999	0.34623
	8.8	8.9	8.4	8.7	8.23	9.2
	0.39	0.29	0.35	0.24	0.34	0.33
Andhra Pradesh	0.048869	0.151092	0.97876	0.45335	0.53432	0.412738
	8.3	9.2	13.4	14.0	16.1	16.5
	0.22	0.20	0.36	0.32	0.25	0.25
Navi Mumbai	0.73243	0.82344	0.72143	3.72445	0.92345	-0.42353
	8.31	8.62	9.47	9.41	8.23	8.20
	0.15	0.14	0.29	0.21	0.23	0.24

related work, it was found that the deep learning framework provides good accurate results irrespective of the application. In this extension, we employed the ensemble deep learning framework to predict the monthly rainfall in detail. Nine meteorological variables were given as input to the ensemble model. Experimentation was conducted and the outcomes of the ensemble model were related to Bayesian Linear Regression and Decision Forest Regression. The performance of the Ensemble model provides better results while finding the Normalised Square Error. Even though it produces better results, rainfall forecasting needs accurate results. We can promote our research work by applying other traditional machine learning algorithms to improve the results of rainfall forecasting. Studies can also be formulated with the help of articulate monitoring in some areas and extend this to a greater dataset in order to bring better accuracy of prediction.

Data Availability Statement

Data used for this research are openly available from the Indian Meteorological Department Ministry of Earth Sciences Government of India at https://mausam.imd.gov.in/.

Meteorological parameters are included in Khan et al. (2020).

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