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Optimized Preprocessing using Time Variant Particle Swarm Optimization (TVPSO) and Deep Learning on Rainfall Data

Umamaheswari P* & V Ramaswamy

Department of Computer Science and Engineering, Srinivasa Ramanujan Centre, SASTRA Deemed to be University, Kumbakonam 612 001, Tamil Nadu, India

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In the recent past, rainfall prediction has played a significant role in the meteorology department. Changes in rainfall might affect the world's manufacturing and service sectors. Rainfall prediction is a substantial progression in giving input data for weather information and hydrological development applications. In machine learning, accurate and efficient rainfall predictionis used to support strategy for watershed management. The prediction of rain is a problematic occurrence and endures to be a challenging task. This paper implements a novel algorithm for preprocessing and optimization using historical weather from a collection of various weather parameters. The Moving Average-Probabilistic Regression Filtering (MV-PRF) method eliminates unwanted samples with less amplitude from the database. The Time Variant Particle Swarm Optimization (TVPSO) model optimizes the preprocessing rainfall data. Then this optimized data is used for the different classification processes. The preprocessing methods emphasize the recent rainfall data of the time series to improve the rainfall forecast using classification methods. Machine Learning (ML) technique classifies the weather parameters to predict rainfall daily or monthly. These experimental results show that the proposed methods are efficient and accurate for rainfall analysis.

Keywords: Classification, Machine learning, Optimization, Rainfall prediction, Time series

Introduction

Rainfall is essential in hydrology and meteorology since it is an integral element of the water resource ecology. Rainfall, in particular, is the consequence of multi-scale air interactions and is influenced by various external conditions, including thermal power, flow field, and topography. For worldwide water management and climate research, geographical dimensions and different rainfall processes have been developed. Objective labels for training Machine Learning classifiers are high-quality rainfall data obtained through a communication radar detection system.[1] Machine learning techniques ignore environmental variables in upstream and downstream regions, causing accuracy prediction to vary in various places. Quantitative Principal Element Component Analysis (QPECA) is utilized to decrease the number of physical variables used as Multi Layer Perceptron's input. The design of MLP is estimated using a modified greedy algorithm. Conventional backup and recovery learning algorithms[2] are ineffective for processing massive amount of climatic data. So the monthly average of climate parameters is calculated using the Hadoop algorithm.[3,4] Temporary Compression and Discrete Wavelet Transform have been integrated with multiple input artificial neural networks. This approach combines techniques for dealing with large databases and uses 36 predictors, including land and ocean variables, to classify rainfall into floods, normal, deficient, and droughts. Spatial modeling techniques such as supervised learning models, Long Short-Term Memory (LSTM), And Temporal Convolutional Neural Network (TCNN) use Spatio-temporal dataset[6,7] for the prediction process. Its performance is compared with traditional analytical neural network models, statistical modeling approaches, and an interactive ensemble method, besides well-established weather research and forecasting models.

The state-of-the-art LSTM and TCNN systems, which are specialized neural networks for weather forecasting applications, are investigated.[8] Time Variant Particle Swarm Optimization (TVPSO) model is applied for optimizing the filtered rainfall data. The machine learning technique is used to classify the useful attributes of the dataset. Related works and pitfalls of existing systems are discussed in next

*Author for Correspondence
E-mail: pum@it.sastra.edu

section. The proposed methodologies follow it. The later section deals with results and discussions. The paper ends with a conclusion and future scope**.**

Related Work

The review of existing approaches from the literature is discussed in this section. The efficiency of five commonly used machine learning algorithms in predicting climatological factors using monthly information on a regular basis is studied. Results show the prediction accuracy of ML models[9–11] is compared to basic mathematical estimation techniques computed directly from the learning algorithm. Multiple machine learning models have been investigated rainfall prediction over South America.[12] Due to a lack of geography related attributes, numerical weather models cannot accurately predict precipitation patterns in South America. A new classification method for rainfall prediction and an innovative attribute selection technique to reduce the prediction error rate with deep learning forecasting is devised. The Observant Insights Tabular Learner (OITL)[13] neural network is used to create a rainfall prediction model based on multimodal connections between weather conditions. Seasonal changes cause unpredictability in rainfall estimation, and feature extraction[14] methods are employed to decrease this issue. The forecasting capability of Regression Analysis, Period Memory based model is proposed that outperforms existing advanced machine learning systems.

Rainfall forecasting in the short or medium term is a crucial challenge[15] in various environmental activities, such as fertilizer application and flood risk assessment. A Deep Convolutional Neural Network (DCNN) is developed using a combination of rainfall radar images and wind velocity provided by weather prediction models to enhance forecasts. Artificial Intelligence[16] is a rapidly evolving discipline in computer application areas. It can be used to analyse the vast volume of fragmented and heterogeneous data and uncover deep and complicated relationships between these data. TRU-NET (Temporal Recurrent U-Net) model[17] is suited for representing zero-skewed weather patterns, and it is proposed to minimize the errors during prediction. Experiments demonstrate that loss-trained models regularly achieve lower RMSE and MAE ratings than a Deep Learning algorithm. Particle Swarm Optimization-based Extreme Learning Machine (PSO-ELM) model can forecast stabilized composite bases' behavior in wet-dry phases. This model has been compared with PSO-ANN and Arithmetic ELM models (AELM).

Different predictor methodologies have been used to improve the accuracy[18,19] of a new generation of stochastic monthly rainfall forecasting algorithms. Proper attribute selection of rainfall data leads to accuracy in the learning process. The existing system has investigated the different forecasting models based on Continuous Wavelet Transform (CWT) in yearly rainfall data. A Hybrid Rainfall Forecasting System (HRFS) has been created by combining Back Propagation Neural Network Classifier with CWT (BPNNC-CWT). Much research has been carried out in recent years to improve the prediction performance of soft computing techniques. Wavelet Transform (WT) is a multi-resolution signal identification and management tool that describes a signal in time and space. Time series modeling approaches involving wavelets have attracted much attention in meteorological modeling and prediction. Some of the pitfalls of the existing system have been identified and listed below.

- It is generally difficult to predict the weather accurately.
- Monitoring is costly due to the existence of several characteristics from different sources.
- It is too costly to purchase the machines required for carrying out millions of computations.
- If the weather does not match with the predicted, the meteorologists will be blamed.
- The accuracy of the prediction may be impacted by climate change.

When the modeling results are compared, it is clear that preprocessing improves the outcomes over the primary case with no preprocessing. To produce the optimum model for the intended issue, it is advised to apply both normalization and stationary approaches[20], as well as other preprocessing procedures. Harris Hawks Optimization method (HHO) implementation using Least Squares Support Vector Machine (LSSV), ANN, and MLR to build alternative models to increase performance accuracy.[21] In basins with inadequate ground-based rainfall data, an Advanced Microwave Scanning Radiometer for the Earth Observing System (AMSRS)[22,23] precipitation data is used in a modeling technique. Simulation findings indicate the benefits of the combined SVM-PSO[24] model employed in learning algorithms. This approach offers the potential for development. Using deep belief networks to anticipate meteorological precipitation is a new trend in weather forecasting.

Deep belief networks[25] turn the original space's feature data representation into a new space of features containing semantic characteristics to increase predictive performance. In months with low yearly averages, the Australian Community Climate and Earth-System Simulator-Seasonal Prediction System,[26,27] (ACCESS) performed better. The outcome is promising and has the potential to be widely applied in this sort of application. A multilayer perceptron[28]model is preferred for prediction and an autoencoderis suited for minimizing error during the learning phase. When this model is compared to prior approaches, it shows an increase in the capacity to estimate the cumulative daily rainfall for the following day. Because of better accuracy, the ARIMA[29,30] model is optimal for predicting rain attenuation for Ku-band satellites operating at 12 GHz. The error is tested using an error matrix (MSE, RMSE, and MAPE) that increases with increasing window size.

Proposed Methodology

This suggested technique aims to explore the filtered rainfall data using adaptive filters to improve the quality of climate forecasts. In this paper, Moving Average-Probabilistic Regression Filtering (MV-PRF) is proposed for preprocessing of rainfall data. Moving Average Filter is used to smooth out unpredictable variations in the data and preserve the precise data.

Dataset Description and (MV-PRF)

Real weather data with 145460 rows and 22 data features are acquired from Kaggle (https://www.kaggle.com/jsphyg/weather-dataset-rattle-package) for this investigation. Because the initial dataset is gathered and recorded by weather stations (Commonwealth of Australia 2010, Bureau of Meteorology) through rain radars and satellite photos, it must be evaluated and processed before the weather prediction model can be established. A new attribute selection technique aims to locate a relevant subset of attributes to utilize in model creation. There are several approaches to attribute selection. The Moving Average-Probabilistic Regression Filtering (MV-PRF) method removes zero mean noise variance in the collected data from the meteorological department. Different attributes are considered in the rainfall database, like minimum temperature, maximum temperature, rainfall data, evaporation, sunshine, wind speed, sunshade, and humidity. The sample weather dataset is listed in Table 1. Optimization and machine learning classification techniques are used to select attributes. The framework of the proposed methodology is shown Fig. 1. The key objective of this paper is to assess new preprocessing approaches in nonlinear time series forecasting. Patterns and seasonal patterns are included. Using the MV-PRF procedure, the initial N-dimensional matrix will be changed into a K-N-dimensional matrix. This involves the normalisation of a given set of attributes. Rainfall data is normalized using Eq. (1).known as Min-Max normalisation.

$$RFdata' = RFdata - \min(RFdata) / (\max(RFdata) - \min(RFdata) \quad \ldots (1)$$

RFdata' is the normalized rainfall data, min (RFdata) and max (RFdata) could be the lower and

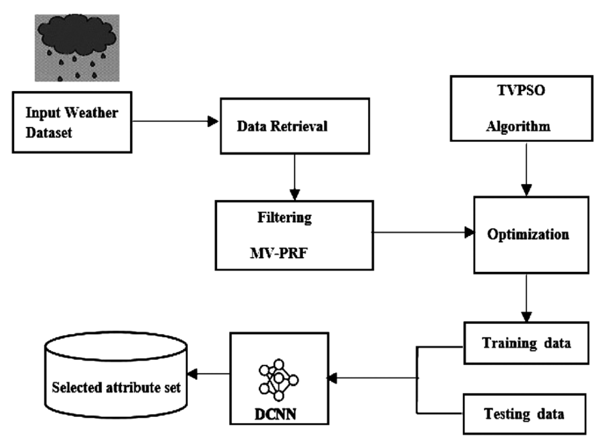

Fig. 1 — Framework for proposed approach

Table 1 — Partial weather dataset

Date	Location	Min. Temp.	Max. Temp.	Rainfall	Evaporation	Sunshine	Humidity 3 pm	Pressure 3 pm
7/22/2008	Hobart	3.3	10.9	5.2	1.6	6.2	54	1022.2
1/10/2009	Melbourne Airport	10.7	23.6	0	7.2	10.2	46	1010.3
5/7/2010	Wagg	6.2	17.6	0	0.6	7.3	57	1022
1/14/2011	Canberra	17.4	26.1	3.8	2	1	55	1007.5
2/2/2012	Tuggeranong	12.4	16.8	0	NA	NA	75	1009.8
1/23/2014	Sale	8.4	26.6	0	7.4	12.2	41	1016.8
3/4/2015	Dartmoor	9.5	21.6	0	6.2	4.3	57	1013.7
7/11/2016	Walpole	9.1	12.8	9.4	NA	NA	66	1021.5
3/17/2017	Perth Airport	9.2	24.8	0	4.8	10.1	55	1010.8

upper values of each column in the dataset and normalized using maxima absolute normalization. The result of maxima absolute normalization can be defined as the value range of [0, 1].

$$RFdata' = RFdata/abs(max(RFdata)) \quad \ldots (2)$$

Where RFdata′ indicates the normalization input rainfall data whereas max(RFdata) denotes the maximum value of every column in the rainfall dataset.

There are M entries in a raw input database with M rows and N+1 columns; each entry includes N distinct characteristics and a forecast goal. Rainfall forecasting is a quantitative approach that divides data characteristics into multiple elements, each representing one of the fundamental patterns. After preprocessing, the rainfall data set is then optimized to improve the rainfall data characteristics. Time Variant Particle Swarm Optimization (PSO), a prominent parameter optimization technique is also used in this work. Particle Swarm Optimization (PSO) is a kind of swarm intelligence approach that was extensively used four decades ago. Because of its simplicity and capacity to optimize complicated restricted objective functions in multimodal search spaces, The PSO is a population-driven stochastic optimization technique that has recently seen extensive applications in improving key challenges. Each possible alternative is referred to as a particle in the PSO, and each group of particles constitutes a population.

Particle stores the place linked with its best fitness ever in personal memory. Furthermore, the location is linked with the best value acquired thus far by any particle. These values are updated in each iteration, and each particle alters its velocity to travel stochastically toward them. Each network contains many levels including input nodes, output nodes, and one or more hidden nodes each with numerous layers. Each neuron in one layer connected to neurons in other levels via output layer. It receives summed weighted inputs and bias components from connected neurons in the preceding levels. An error back-propagation approach is used to construct the connection weights that connect distinct network nodes. Adjusting the weights of the links in the network to reduce error criteria yields a trained response. Validation can therefore help to decrease the risk of imbalanced datasets.

DCNN Model

In this model, input layer is the first layer and the activation function is the last. The middle levels are hidden layers, and each layer contains multiple layers are depicted in Fig. 2. DCNN is a neural network that can extract hierarchical information from local interactions between nodes.

In this proposed approach, DCNN is recognized as an acceptable model when input data incorporates characteristics such as pressure and temperature at different times, such as 3 pm, 7 pm, and so on, A cost function represented by Eq. 3, is defined to evaluate the performance of the network. Input layer has N1 nodes, which reflect the input data's dimension. N2 and N3 neurons are found in the hidden layers 1 and 2, respectively. The output layer has N4 neurons, which indicate the data output. Each level has a biased node in addition to the output nodes. It stands out because to its unique characteristics in automated learning, which can learn implicitly through training data and perform feature extraction using convolution kernels.

$$C(w,b)=\frac{1}{2n}\sum_x [y(x)-a^2]^2 \quad \ldots (3)$$

Here **w** denotes the network's total weight, **b** denotes all biases, **n** denotes the total number of training inputs, and **a** denotes the actual output. The

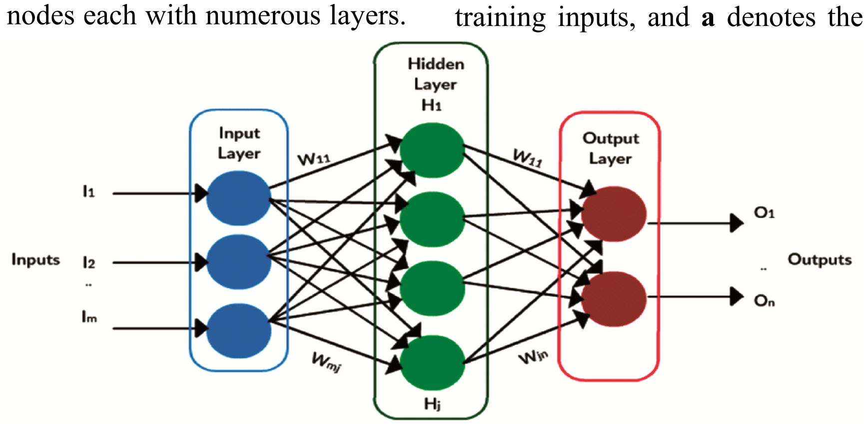

Fig. 2 — Basic structure of DCNN

actual output has been determined by the variables x, w and b. Note that all the components in the summation are non-negative. Here C (w,b) is non-negative. Furthermore, C(w,b)=0 for all 'n' inputs when the objective function y(x) is relatively identical to the total performance, n. To minimize the cost C(w,b) as a function of weight and biases, the learning algorithm must be able to discover a set of weights and biases that cause the cost to become as low as possible. Gradient descent is the algorithm used to do this. Gradient descent, in other terms, is an optimization technique that continuously bends its parameters to reduce an objective functions to its local optimum. Here learning rate is denoted by (η). The set of equations, which are used by the gradient descent technique to set the weights and biases, are as follows.

$$W^{new}=W^{old}-\eta\frac{\partial C}{\partial W^{old}} \quad \dots (4)$$

$$b^{new}=b^{old}-\eta\frac{\partial C}{\partial b^{old}} \quad \dots (5)$$

When the training data is sufficiently vast, however, the gradient descent technique may not be very useful. As a result, a stochastic variant of the method is employed to improve the network's effectiveness. Minimal number of iterations is required in Stochastic Gradient Descent (SGD) to discover efficient solutions to optimization issues. In SGD, a minimal number of iterations is all that is required to optimal solution. The set of equations, which are used in the SGD technique are as follows.

$$W^{new}=w^{old}-\frac{\eta}{m}\frac{\partial C_{xj}}{\partial w^{old}} \quad \dots (6)$$

$$b^{new}=b^{old}-\frac{\eta}{m}\frac{\partial C_{xj}}{\partial w^{old}} \quad \dots (7)$$

Minimum and maximum values are represented by min_Data and max_Data, respectively

$$z=\frac{Data-min_{Data}}{max_{Data}}-(max_{Data}) \quad \dots (8)$$

Results and Discussion

The general structure includes neural network models along with some cutting-edge techniques. Various parameters are used for preprocessing the rainfall prediction model. Mean square error and root mean square error are computed. The various rainfall prediction data attributes (minimum temperature, maximum temperature, rainfall, etc.) are shown in Fig. 3. The model's initial determinants include 21 forecasting parameters with 145460 occurrences correlating to the months between the years studied (2008–2017). Zero variances indicate whether the occurrence is more favourable or unfavourable.

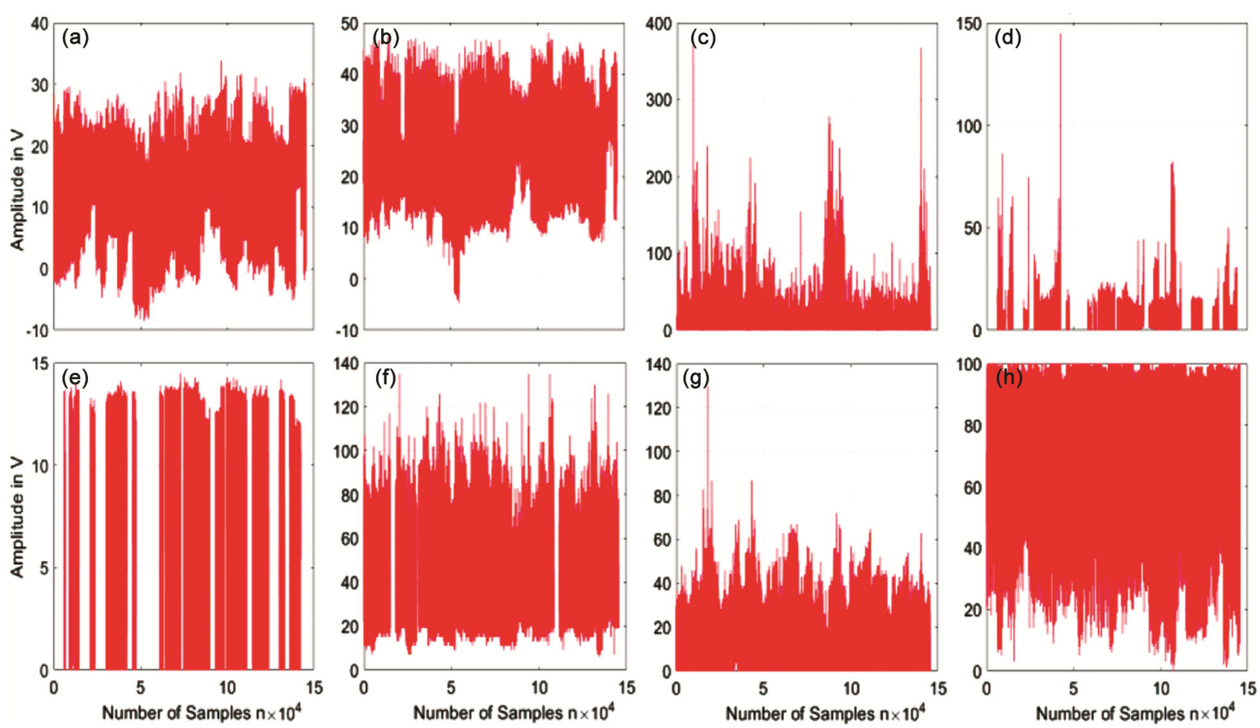

Fig. 3 — Rainfall prediction data attributes: (a) Minimum temperature, (b) Maximum temperature, (c) Rainfall, (d) Evaporation, (e) Sunshine, (f) Wind speed, (g) Sun shade, and (h) Humidity

Experimental results are carried out using MATLAB simulation tool. The results are discussed in terms of graphs and numerical values. A useful mathematical model has been developed for rainfall forecasting based on learning models for regional rainfall forecasting in order to tackle both classification and regression issues.

These attributes are taken into account for preprocessing. The filtered rainfall prediction data is qualified for further Optimization and classification of useful attributes. In the proposed methodology, various classification methods are used for comparison purposes. Deep Convolutional Neural Network (DCNN) is proposed for classification of useful attributes from rainfall data. K Nearest Neighbor (KNN), Back Propagation Neural Network (BPNN), Iterative Convolutional Neural Network (ICNN) and Convolutional Neural Network (CNN) are all compared with DCNN. The performance of DCNN is turned out to be better than other methodologies in terms of error reduction. The data preprocessing is used to improve the quality of rainfall data to predict rainfall further. The combination of MV- PRF and TVPSO provides improved attributes of rainfall data as given in Table 2. Moreover, The filtered rainfall prediction data using MV-PRF filtering technique is shown in Fig. 4. Zero mean variance from rainfall prediction data is eliminated. The input rainfall prediction data has eight attributes. After DCNN classification, it is reduced to four attributes, namely minimum temperature, rainfall data, wind speed data and humidity. These four attributes are classified as useful for further rainfall prediction. After elimination of unnecessary data from database, metrics like Mean Square Error and Root Mean Square Error are computed. It is taken into account for the classification of attributes and prediction model. The comparison of the error rates of several neural network techniques to DCNN is shown in Table 3.

Table 2 — MV- PRF and TVPSO Optimization performance

	Min. Temp.	Rainfall data	Wind speed	Humidity
Before MV-PRF - TVPSO	13.3898	18.3878	17.3987	16.3987
	11.3989	12.3897	16.3989	23.3983
	23.3989	29.3989	15.3898	13.3987
	17.3875	27.7680	54.3897	46.3987
	16.3989	17.3987	26.3896	53.3854
After MV- PRF - TVPSO	1.3987	2.3987	1.3983	2.3498
	1.3989	1.3878	1.3987	1.2936
	1.0398	1.3383	1.3893	1.2568
	1.2893	1.5909	1.2898	1.3438
	1.6739	1.8999	1.3849	1.3898

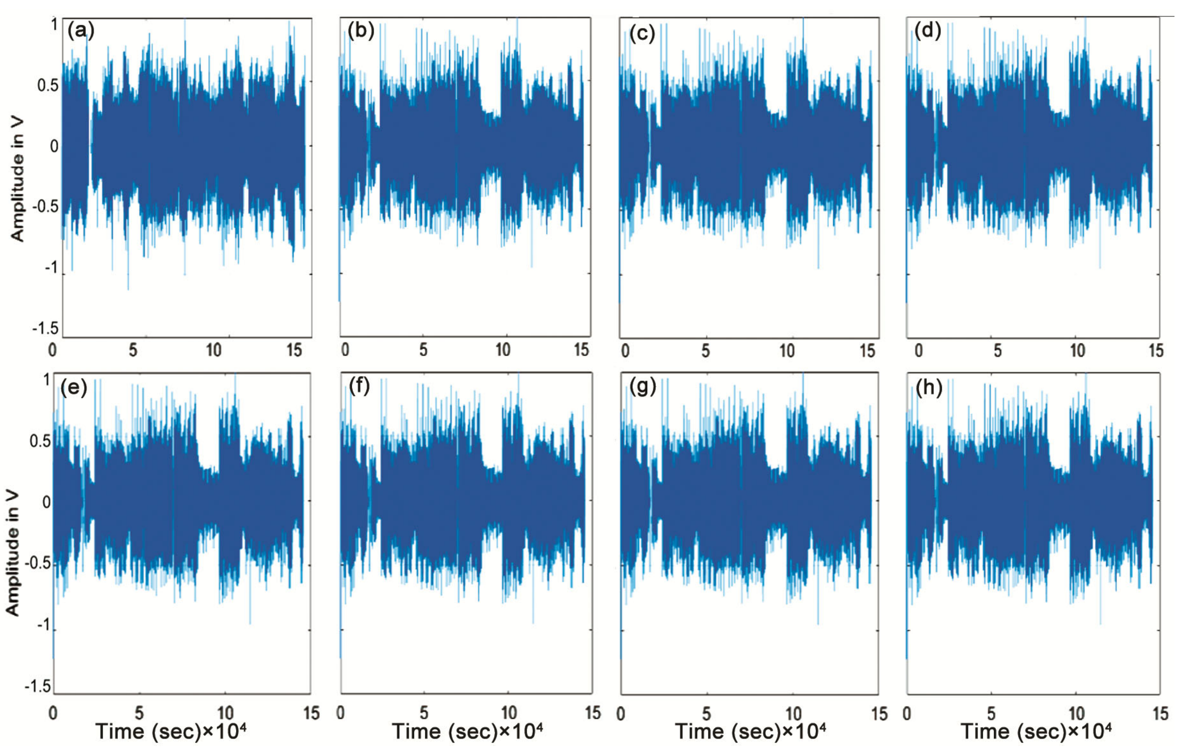

Fig. 4 — Filtered rainfall prediction data using MV-PRF filter: (a) Minimum temperature, (b) Maximum temperature, (c) Rainfall, (d) Evaporation (e) Sunshine, (f) Wind speed, (g) Sun shade, and (h) Humidity

Table 3 — Error Rate Vs. Number of Epochs of DCNN

S. No	Epochs	KNN	BPNN	CNN	ICNN	DCNN
1	2	0.5628	0.4690	0.4020	0.3518	0.3127
2	4	0.2288	0.1907	0.1634	0.1430	0.1271
3	6	0.0595	0.0496	0.0425	0.0372	0.0331
4	8	0.0077	0.0064	0.0055	0.0048	0.0043
5	10	0.0003	0.0003	0.0002	0.0002	0.0000

Table 4 — Accuracy Vs. Number of epochs of DCNN

S. No	Epochs	KNN	BPNN	CNN	ICNN	DCNN
1	2	63.8081	63.8081	66.1714	68.7165	71.4651
2	4	68.3386	68.3386	70.8696	73.5954	76.5392
3	6	69.9832	69.9832	72.5751	75.3665	78.3811
4	8	70.4663	70.8244	73.4475	76.2724	79.3233
5	10	71.0928	71.2930	73.9335	76.7771	79.8482

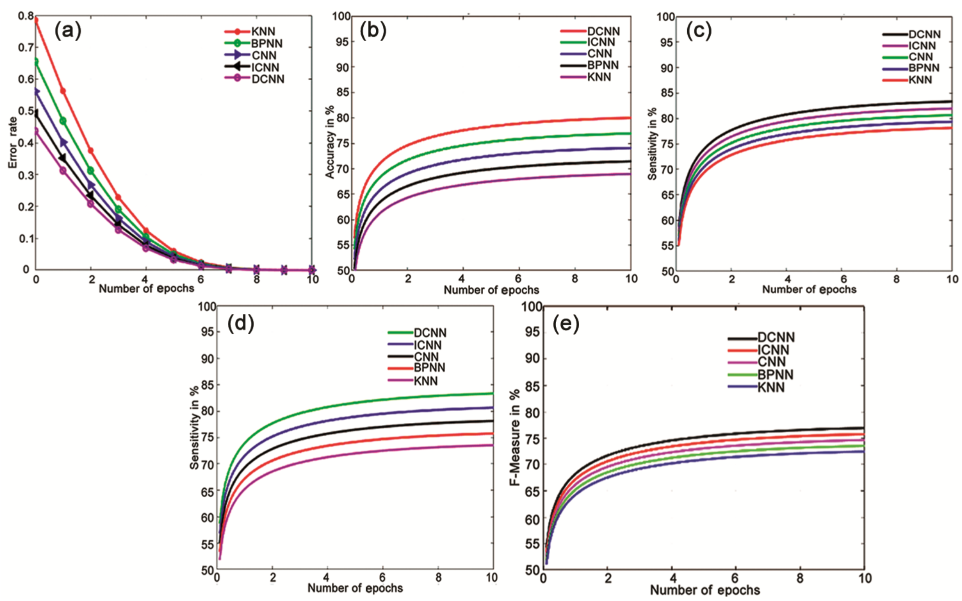

Fig. 5(a–e) — (a) Comparison of Error Rate Estimation, (b) Comparison of accuracy, (c) Sensitivity in percentage comparison, (d) Specificity in percentage comparison, and (e) F- Measure in percentage comparison

The number of epochs is a hyperparameter, specifying how often the learning algorithm will run over the complete training dataset. Each observation in the training dataset has undergone one epoch, which indicates that the underlying model parameters have been updated. Each epoch is made up of one or more sets. It can be seen that as the number of epochs rises, the neural network's error rate reduces. The proposed DCNN error rate decreases to a null value at epochs equal to 10. Other neural network approaches have a higher error when compared to DCNN.

The error rate estimation of various algorithms with proposed approach is compared and it is shown in Fig. 5(a). The DCNN accuracy rises with the number of epochs. Precision and recall are both taken into account while calculating the F1 Score. The accuracy of DCNN is observed to be better than other neural network performance and it is shown in Table 4. The comparison between a number of epochs and accuracy in percentage is shown in Fig. 5(b). The percentage of DCNN is observed to be higher at nearly 80% when compared to other methodologies. Other methodologies have an accuracy of have less than 80%. The sensitivity in percentage comparison between DCNN and KNN, BPNN, CNN and ICNN is shown in Fig. 5(c). It is observed that the sensitivity of DCNN is greater than 80% whereas other methodologies reach lesser sensitivity values. Specificity in percentage comparison is shown in Fig. 5(d). The proposed methodology has reached specificity of greater than 85% where as other methods have less than 85%. F-Score of DCNN compared to KNN, BPNN, CNN and ICNN is shown in Fig. 5(e). F-Measure is often referred to as F-Score.

Conclusions

In this paper, novel algorithms have been proposed for preprocessing of rainfall prediction data. Machine learning plays a significant role in categorizing valuable properties of rainfall forecast data. The conclusion could be summarized as follows. The rainfall prediction dataset has been considered for preprocessing purpose. Moving Average-Probabilistic Regression Filtering (MV-PRF) eliminates zero mean values from the rainfall prediction data. The Time Variant Particle Swarm Optimization (TVPSO) rule is used for Optimization. Deep Convolutional Neural Network (DCNN) is used to classify vital attributes from rainfall prediction data. This work can further be extended to clustering rainfall data for forecasting daily rainfall prediction based on valuable features. In the future, our objective is to enhance the prediction model's performance by incorporating global and regional meteorological patterns such as sea surface temperature, global wind circulation, and soon.

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Conflict of Interest (COI)

The authors declare that they have no conflicts of interest to report regarding this present work.

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