An Adaptive Salp-Stochastic-Gradient-Descent-Based Convolutional LSTM With MapReduce Framework for the Prediction of Rainfall

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Abstract

Rainfall prediction is considered to be an esteemed research area that impacts the day-to-day life of Indians. The predominant income source of most of the Indian population is agriculture. It helps the farmers to make the appropriate decisions pertaining to cultivation and irrigation. The primary objective of this investigation is to develop a technique for rainfall prediction utilising the MapReduce framework and the convolutional long short-term memory (ConvLSTM) method to circumvent the limitations of higher computational requirements and the inability to process a large number of data points. In this work, an adaptive salp-stochastic-gradient-descent-based ConvLSTM (adaptive S-SGD-based ConvLSTM) system has been developed to predict rainfall accurately to process the long time series data and to eliminate the vanishing problems. To optimize the hyperparameter of the convLSTM model, the S-SGD methodology proposed combine the SGD and the salp swarm algorithm (SSA). The adaptive S-SGD based ConvLSTM has been developed by integrating the adaptive concept in S-SGD. It tunes the weights of ConvLSTM optimally to achieve better prediction accuracy. Assessment measures, such as the percentage root mean square difference (PRD) and mean square error (MSE), were employed to compare the suggested method with previous approaches. The developed system demonstrates high prediction accuracy, achieving minimal values for MSE (0.0042) and PRD (0.8450).

Keywords

ConvLSTM, MapReduce, MSE, PRD, S-SGD.

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I. Introduction

Agriculture is the broadest economic sector that has contributed to the socio-economic development of India. The economy and climate are the primary factors having the major impact on agriculture [1]. Crop production is enhanced using advanced agricultural techniques, which assist the monitoring system and provide information regarding the environment. Crop yield information is essential for industrial operation as the product of agriculture is used in industries. Decisions regarding the supply chain are planned by estimating the crop production accurately. Enhancing the crop yield is as important as monitoring the environmental factors. Agriculture depends on rainfall, cultivation, irrigation, fertilizers, pesticide weeds, soil, climate, temperature, harvesting, and other factors [2]. The growth of crops becomes a critical challenge in the absence of adequate rainfall. It is important to know how much water is needed to get the right amount of water for the irrigation process [3].

The Indian Meteorological Department (IMD) divides the climatological seasons into four categories: summer or pre-monsoon, winter, monsoon, or rainy season, and fall or post-monsoon. Considering December to February, the winter season is in full swing. From March to May, the summer of pre-monsoon season begins. We experience the rainy season, sometimes known as the monsoons from June through September. The southwest summer monsoon, which is humid generally starts during late May or early June, and it moves slowly. The monsoon rains begin to fade at the starting period, especially in the early October. South India gets more rainfall than the rest of the nation. The post-monsoon season begins in October–November. The Northeast Monsoon is when Tamil Nadu receives most of its yearly rainfall. The agricultural sector predominantly depends on

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the monsoon. The forecasting of the amount of rain in a specific area is a tedious process. It requires careful observation of the atmospheric conditions and the development of models that stimulate cumulus cloud interaction and atmospheric conditions, leading to a high degree of complexity [4].

In addition, rainfall prediction is even more difficult. Estimating the rainfall comprises investigating the groundwater quality, soil features, land features, and other aspects. Misleading conclusions occur if any of the factors are neglected without any consideration. For example, when estimating the required amount of water for agriculture, if the amount of rainfall in the particular area does not account for and the water is more than predicted for the specific area, then water-logging occurs, resulting in salinity, which, in turn, reduces the crop yield.

On the other hand, if the water is less than indicated, it leads to under-irrigation, which results in reduced yield efficiency. As a result, predicting the appropriate quantity of rainfall is of paramount importance for the irrigation of crops [5]. Physical and data-driven models [6],[7] are the two types of models that are used for predicting rainfall. Physical models use physical principles to simulate the physical processes that contribute to the rainfall process, whereas data-driven models forecast the future based on historical data [8].

Agriculture primarily depends on the soil condition and climatic features. There is a significant need for a system or model that can reliably forecast precipitation. That's why we're working on it in the first place: to create a rain forecasting system that uses deep learning and the MapReduce framework. This approach contributes by passing the data into an adaptive salp-stochastic-gradient-descent-based convolutional long short-term memory (adaptive-S-SGD-based ConvLSTM) network. The optimal weights have been carefully chosen by the adaptive S-SGD algorithm.

Following are the challenges found in the approaches corresponding to the prediction of rainfall confront:

- Analysis of precipitation using non-linear historical time series data is time-consuming [9].
- The dynamic nature of the weather is one of the challenges that need to be considered during weather forecasting as the weather data varies with time and space. The computation of the regression coefficients based on the past models during the training period and the observed forecast that neglects the dynamic nature of the weather is required [9], [10].
- The deviation in the spatial and the temporal rainfall conditions, the inaccurate initial conditions, and the complexity related to the physical process also pose a challenge for the prediction [11].
- Even though there are many tools for weather forecasting, predicting the weather data with a large structure and volume is a massive task. Thus, the prediction of weather using weather data is not an easy task [12].

The following are the most important contributions:

- The goal of this work is twofold: (1) to develop an adaptive S-SGD-based ConvLSTM system for predicting rainfall, and (2) to disseminate this knowledge to farmers so that they may maximise their crop yields.
- To demonstrate the superior performance of the proposed model, we have compared the results of the adaptive S-SGD-based ConvLSTM model to those of the S-SGD-based ConvLSTM model, ConvLSTM, and CLR.

In this study, we have used an adaptive S-SGD-based ConvLSTM system for rainfall prediction. The adaptive prediction model, built within the mappers of the MapReduce framework, is given to be the input data. The deep LSTM can be trained optimally by considering the optimal weights obtained using the adaptive S-SGD algorithm. The algorithm is evolved by hybridizing the adaptive concept in the S-SGD algorithm. The hybridized algorithm is applied to ConvLSTM to adopt the best training in the LSTM system.

A serious concern around the world is rainfall prediction. It has attracted the attention of industries, the government, the research, and development sector, and also entities related to risk monitoring and management. Precipitation forecasting using an adaptive neuro fuzzy inference system-genetic algorithm (ANFIS-GA) was developed by Wahyuni et al. [13]. Although the ANFIS-GA model predicted the rainfall accurately, this technique failed to determine the crop budding period. Hussain et al. [14] designed a dynamic, self-organized multilayer neural network model to forecast naturally occurring signals. They used this method for clustering by changing the output layer with the backpropagation algorithm. However, this method required global optimization algorithms to achieve accurate predictions. Bhomia et al. [15] modeled a dynamical-model-selection-based multimodal ensemble model to predict the amount of rain during the rainy season. This method removed the non-normality of the predictors using transfer functions. However, the prediction rates need to be improved. Haidar and Verma [16] developed a deep convolutional neural network to predict rainfall. Although this method performed better with high annual averages, the diversities in the models need to be combined with the ensemble techniques. Zhou et al. [17] tried the deep learning method for predicting the rainfall for diverse types of convective climate. Poornima and Pusphalatha [18] proposed a recurrent neural network (RNN) based on intensified LSTM towards rainfall prediction. This work's limitation is that the accuracy improvement is small compared to the existing LSTM and RNN methods. Anh et al. [19] proposed a method based on a deep learning model incorporated with LSTM and the feedforward neural network (FFNN) for precipitation downscaling for regions in Vietnam. Diop et al. [20] investigated using an innovative hybrid method, namely multilayer perceptron-Wale optimization algorithm, to predict the annual rainfall and used three lags. Khan and Maity [21] proposed a hybrid deep learning approach based on a multilayer perceptron (MLP) and the grouping of a one-dimensional convolutional neural network for multi-step-ahead daily rainfall prediction. Their approach combines an MLP and the support vector regression method. Zhang et al. [22] suggested a short-term rainfall forecasting model based on MLP. Putra et al. [23] presented a deep autoencoder-based semi-convolutional neural network for yearly rainfall prediction. Hewage et al. [24] suggested a lightweight model named a data-driven weather-predicting model by exploring the temporal modeling approaches of LSTM and temporal convolutional networks. They compared their performance with machine learning and ensemble methods. Neural networks have been combined with many other models to achieve accurate prediction power. The variation in the predicting power was to use the unique features of each model to identify the different patterns in the data. A severe restriction of using neural networks is the non-interpretation of the data analysis model. The conventional fuzzy systems may not have any learning procedure to shape the analysis model. The general circulation model (GCM) does not provide an accurate portrayal of the local climate. In addition to this, issues also exist in the various rainfall prediction techniques in agriculture. Many machine learning models use the gradient descent algorithm to tune and select the parameters. SGD is used in the fast computation of the requirements. The SGD algorithm might not achieve accuracy, but it fluctuates around the region close to the global minimum. When combined with the techniques such as swarm optimization, it provides optimized results. Artificial-neural-network (ANN)-based methods have been extensively used for predicting rainfall in various regions of the world. It is observed that RNNs such as LSTM enhance the explicit management of order between the observations whenever the knowledge of a mapping function is obtained from the inputs to the outputs. This LSTM provides native support for the sequences. To do defensible time forecasting, methods such as LSTMs [25] and hybrid LSTMs can be used. Ridwan et al. [26] suggested a rainfall forecasting model using machine learning. The prediction obtained using their model did not monitor the water level in the reservoirs. Methods such as Bayesian linear regression, boosted decision tree regression, and neural network regression were used in the process. Here, the daily error rate and the monthly error rate were calculated. The primary focus of the authors was to introduce the RAIN-F+ dataset, and only the early fusion methods were used. The results thus obtained were validated only for the radar observations. Jaseena et al. [27] executed a deep survey on the techniques based on deep learning to process massive datasets for rainfall prediction. Their study covered the idea that only small datasets were used in most of the works and that massive datasets needed to be utilized. The evaluation of stability was not addressed in this work. Ahmed et al. [28] aggregated the antecedent lag memory of the climate node indices and the rainfall. A hybrid LSTM method was used in the process and was influenced by the low-frequency variability of the climate indices. This type of forecast was applied for flood forecasting and irrigation scheduling. Sun et al. [29] proposed a convolutional 3D gated recurrent unit model to predict rainfall intensity over a short period of time based on machine learning. The limitation of this work is that it has shortcomings in the prediction of rainfall within an hour. Tran et al. [30] suggested an improved rainfall prediction model using the combined preprocessing methods and FFNN. It provided better results compared to the conventional models but exhibited poor results compared to the hybrid models. Lin et al. [31] proposed a hybrid deep learning algorithm and its application to streamflow prediction. Their model comprised the first-order difference, FFNN, and LSTM. The limitation of this work is the short lead time. Velasco et al. [32] suggested week-ahead rainfall forecasting using the MLP neural networks. In this work, the hidden neurons are limited, and thus, the performance is observed to be minimal compared to the existing methods. Dewitte et al. [33] proposed methodologies related to weather forecasts based on artificial intelligence techniques. The model gave better results when machine learning and deep learning features were incorporated. Hussein et al. [34] demonstrated the importance of using well-grounded statistical techniques and compared their analysis results with various predictive models based on machine learning. The limitation of this work is that the authors have used only a single parameter prediction that is based on the spatiotemporal features, and the applicability of their model is limited in most of the cases. Yan et al. [35] proposed a rainfall forecast model based on the TabNet model. The reliability of the model was good, and if the addition of more data and parameter tuning had been done, the robustness could have been increased. Convolutional LSTM plays a significant role in the time series data analysis. Deep neural networks can accurately predict rainfall. The salp swarm algorithm (SSA) can be used as one of the better prediction algorithms. The hybrid algorithms provide better forecasts than the individual algorithms. Thus, we have incorporated the SSA and the SGD algorithms [34] based on a convolutional neural network to predict rainfall that will support the farming community and agriculture. In 2018, Yang and Yang [36] proposed, a modified CNN algorithm with dropout and SGD optimizer to enhance feature recognition, reduce CNN time-cost. Achieved high recognition rates on MNIST, HCL2000, and EnglishHand datasets, outperforming other methods. Table I shows the literature analysis of the current trends.

From the analysis of the existing works, we can conclude that the traditional approaches take a long time to process, limited data is used and needs more computational requirements. Neural Network has been used in combination with many other models to give a better prediction. The goal of combining these forecasting models was to take advantage of each one's strengths to predict future events more accurately. One major drawback of Neural Networks is that the underlying data analysis model might not understand the results. The analysis model used by traditional fuzzy systems cannot be learned. General circulation models (GCM) fail to accurately portray the regional climate. Also covered are the difficulties encountered by various agricultural rainfall prediction methods. Gradient Descent is widely used in ML models for parameter selection and tuning. When a rapid computation is essential, SGD is used. While the SGD may not be able to pinpoint an exact value, it does tend to float around the neighbourhood of the global minimum. When combined with the techniques like Swarm optimization, it provides optimized results.

The ANN based techniques has been used for a long period of time to predict the rainfall in various regions of the world. It is observed that, the Recurrent Neural networks like the LSTM adds explicit handling of order between the observations, whenever the learning of a mapping function happens from inputs to outputs. This LSTM gives the native support for the sequences. To do defensible time forecasting, methods like LSTMs and Hybrid LSTMs can be used. Convolutional LSTM plays a major role in the times series data analysis. Deep Neural Networks are likely to be used in the prediction of rainfall and is proved to give a better prediction. The Salp Swarm Optimization Algorithm can be used as one of the better prediction algorithms. The hybrid algorithms have given better predictions than the individual algorithms. So, we have incorporated the SSA along with the Stochastic Gradient Descent algorithm based on a convolutional neural network for the prediction of rainfall that will be a support to the farming community and agriculture. Deep Learning, when applied to Machine Learning, offers insightful replacements for analysing massive data sets and is useful for autonomous feature selection. To analyse data in real time and generate reliable findings and analysis, Deep Learning has developed fast and efficient algorithms and data-driven models. The ability to foretell precipitation using a variety of methods developed over time. Precipitation forecasting is where Deep Learning algorithms really shine.

What follows is the rest of the paper's outline: The ConvLSTM technique based on S-SGD has been addressed in Section II. Discussion and analysis of the results are presented in Part III. In part IV, we draw a final conclusion.

II. Methods

For planning agriculture, rainfall prediction plays a major role. The existing rainfall prediction methods faced issues while dealing with big data. Hence, in this research, the MapReduce framework is used to overcome the issues related to big data, such as parallel computing and computational complexity. The MapReduce framework used the adaptive S-SGD-based ConvLSTM networks for the prediction of the rainfall. The data regarding the weather is given as the input to the framework, which contains both the map and reducer functions. Here, weather data is considered as time-series data and its large amount of data is given as input for dealing with the rainfall prediction process. The MapReduce framework can be used to solve the complexities associated with big data in an efficient manner. It also has the capability to perform parallel computing processes.

A. Adaptive S-SGD Method Towards Training the ConvLSTM Network

1. ConvLSTM Model

Because of its ability to highlight what is most obviously present in the field of view, CNN is commonly employed in feature engineering. LSTM has the characteristic of increasing in size with the passage of time, making it a useful tool for time series analysis. With the capabilities of CNN and LSTM in mind, we create a model for predicting rainstorms using CNN with an LSTM. The main

TABLE I. Literature Survey of the Methodologies, Approach, and Limitation

Research	Objectives	Methods used	Approach	Dataset	Result	Limitation	Advantage
(Janarthananet al. 2021) [37]	The primary objective of this research is to support people by informing them about the unlikeable natural catastrophes.	Fuzzy logic is used to build effective applications or fuzzy base systems to continuously control and monitor the automatic stream engine. Mainly, qualitative, and imprecise expressions have been used in this research to predict rainfall using a fuzzy base system.	Classical controller approaches that are also known as a "point to point control system" have been used in the research to control and range the system.	The US Department of Agriculture (USDA) scan data and rainfall data is used in this research.	As per the dataset, the rainfall volume, like temperature, wind speed, and humidity, is high resulting in heavy rainfall has taken place.	Often, predictions (temperature estimation) may not be accurate because it uses fuzzy datasets.	By predicting the forecast using low-cost FLC, it is possible to support humans and reduce the danger. Therefore, people will be able to receive relevant information about natural incidents in advance.
(Haq et al. 2021) [38]	The main objective of this research is to predict rainfall to expect danger in advance.	Machine learning methods such as Support Vector Machine (SVM), Artificial Neural Network (ANN), and mean absolute error are used in this research study.	LSTM and deep learning approach has been used to predict daily temperature and rainfall.	Indian Ocean Dipole and EI Nino Index data 3.4 is used in this research to enables researchers to predict the certain dangers and rainfall patterns simultaneously.	The prediction using IOD and Nino parameters enables people to identify the rainfall pattern on the 6th week.	Mean arctangent absolute percentage error (MAAPE) can calculate only a limited range of values to predict the actual error.	The El-Nino and IOD characteristics were strong enough to predict rainfall in the Sidoarjoarea of East Java, according to the MAAPE prediction findings, with a value of 0.9644.
(Pham et al., 2020) [39]	The main objective of this research is to build and compare several AI models, such as FIS and adaptive network.	Critical success index (CSI), Probability of detection (POD), Mean absolute error (MAE), and correlation coefficient	Monte Carlo, MLP, decision tree, and K- Nearest Neighbour (KNN) that enables researchers to analyse which model is effective for rainfall predictions.	Training and testing dataset with 3653 sample data.	From January to April, SVM and ANN models have predicted a small volume of rainfall	Accurate prediction of rainfall	There is a chance of predicting the accuracy of rainfall with an appropriate AI model.
(Zhao et al. 2021) [40]	The main objective of this research is to build an AI-based prediction model for calculating the flow of debris.	Model evaluation method, Tsfresh rolling technique, data processing methods, and ensemble methods (gradient descent and extra tree).	Machine learning approach	Cost validation dataset	The researcher has been able to make a good balance between missing alarms and false alarms. Furthermore, this AI-based prediction model is able to reduce the timing of false alarms.	The limited sample size is used to target 70% of random data for training purposes. Otherwise, it can take more time to train more data.	Early warning on the flow of debris and receive accurate rainfall and threshold prediction model.
(Shrestha et al. 2020) [41]	The primary objective is to analyze the use of intelligent computing in robotics.	Kernel method, Network embedding method, and SVM	Parallel random forest and MAV with a low-cost approach	Standard image dataset and GRU network dataset	The robot can monitor the person's activity and their shopping actions.	Calculation in server related index, fingerprint scan through the offline and limited control device.	Data collection through offline mode is possible.
(Chhetri et al. 2020) [42]	The primary objective is the pattern recognition technique for rainfall prediction.	Numeric weather prediction and deep learning methods	Pattern recognition and gated recurrent unit approach	Weather dataset of the period of 1979 to 2009	MLP provides better results about rainfall prediction as compared to the short-term model	Limited computational resources	Improvement of the future prediction model can be possible with the MLP technique.
(Diez-Sierra and del Jesus, 2020) [43]	The primary objective is to predict the long-term pattern of rainfall by utilizing an atmospheric synoptic pattern.	Machine learning and statistical methods	SVM, KNN, k-means, and random forest	Rainfall dataset for managing agency and water planning of Tenerife Island	The f-score metric is beneficial for identifying the accuracy of each model while working with an unbalanced dataset.	Limited sample size	The specific application of the PCA method enables people to receive original and accurate predicted data.
(Zhang et al., 2020) [44]	The main objective is to propose a Tiny RainNet by joining CNN along with "bi-directional long short-term memory."	Optical flow method, machine learning method (SVM), and radar quantitative rainfall prediction (QPF)	Machine learning and big data algorithm	CIKM AnalytiCup 2017	Tiny RainNet requires only 3 ms time to check the whole dataset	Limited data in a single mapRader	This tiny RainNet model provides accurate results about rainfall prediction within a minimum time.

Research	Objectives	Methods used	Approach	Dataset	Result	Limitation	Advantage
(Li et al. 2021) [45]	The primary objective of this research is to develop a data-driven model of food predicting the streamflow with precipitation.	Gridded surface subsurface hydrologic and LSTM	Feature selection approach	US National Elevation, validation, and calibration datasets	The result section discussed that the LSTM model is able to predict rainfall patterns with a good performance level.	Limitation about the computational expense	Accurate prediction of rainfall with LSTM network.
(Hewage et al. 2021) [46]	The main objective of this research is to forecast accurate weather in a reliable NWP that includes WRF and met office models.	Dynamic ensemble method, persistent precision method, and traditional cross-correlation method.	Statistical (quantitative) approach and machine learning approach (feedforward neural network)	Training, testing, and validation dataset.	The result section exhibits that ANN is more reliable in terms of weather forecasting than the cross-validation method.	Ineffective design methodologies for specifying parameters and massive computational requirements.	Advancement of technology and identification of accurate models for weather forecasting is possible in the future.
(Venkatesh et al. 2021) [47]	The primary objective of this research is to develop a rainfall prediction system by utilizing an adversarial network to predict the rainfall data and future rainfall of India.	Financial method, finite difference method, deep learning method, and GAN based method.	ANN and regression approach.	A real rainfall dataset is used in this research study to validate the rainfall prediction system effectively.	The experimental results exhibit that the proposed system offers 99% of accurately predicted results of rainfall.	This proposed system is unable to distinguish the generated data of rainfall from the original data.	The designed GAN model can generate higher predicted rainfall values than the real rainfall data.
(Ren et al. 2021) [48]	The main objective of this research is to predict accurate and timely weather.	Numerical weather prediction (NWP), deep learning, and data-driven methods.	Deep learning-based weather prediction (DLWP) and a data-driven approach are used in this research.	Observation dataset that includes situation analysis data, remote sensing data, and simulation analysis data of the NWP model.	The result section reveals that weather forecasting results vary based on climate change.	Massive computational requirements	The timeliness and accuracy of DWLP are better than the NWP that, supports people in analysing the weather pattern in advance.
(Kumar et al. 2021) [49]	The primary objective of this research is to develop a deep learning-enabled downscaling model for analysing India summer monsoon rainfall data.	Super-resolution convolutional neural network (SRCNN), SVM, and other deep neural methods.	Researchers have tracked traditional SR approach, ML-based approach, and correlation coefficient approach to inspect the summer monsoon rainfall pattern.	IMD gridded dataset	The result section reveals that high-resolution data that is derived from deep learning models provides accurate results rather than linear interpolation.	Limited in spatial resolution	Accurate information based on India's summer monsoon rainfall data can be inspected.
(Fayaz et al. 2022) [50]	The main objective of this work to develop the rainfall prediction method in the worst-case weather scenarios that will be anticipated in advance, and appropriate warnings will be delivered.	Methods from both the nonlinear autoregressive with exogenous input (NARX) neural network and the adaptive grey wolf levenberg-marquardt (GWLM) network were combined.	Trained using the grey wolf optimizer (GWO) and the Levenberg-Marquardt (LM) algorithms	past weather data of Kashmir province, India	The MSE and R-values of the suggested model were examined, and the value of error should be minimized for successful outcomes, as shown in the results section. In addition, performance parameters, including specificity, sensitivity, specificity, recall, accuracy, and Cohen kappa are assessed.	Takes a long time to construct these models and look into the different datasets.	Reaches the best accuracy measures
(Rahman et al. 2022) [51]	novel real-time rainfall prediction system for smart cities using a machine learning fusion technique.	Naive Bayes, K-nearest Neighbors, Support Vector Machines, and Decision Trees are employed. For accurate precipitation forecasting, the framework employs fuzzy logic, also known as fusion, to combine the results of various machine learning techniques.	Machine learning techniques with fuzzy logic	12 years of historical weather data (2005 to 2017) for the city of Lahore	The proposed work is compared with different techniques in terms of Accuracy rate and Miss rate.	The data which will be used for prediction is compromised	higher accuracy

components of this model are the input layer, the one-dimensional convolution layer, the pooling layer, the long short-term memory (LSTM) hidden layer, and the fully connected layer. The complete approach is shown in Fig. 1. All the components of Fig. 1 have been discussed subsequently in this section.

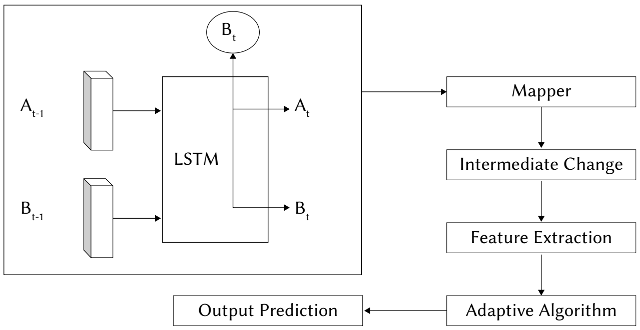

Fig. 1. Computational aspect of the proposed approach.

Here, the ConvLSTM network architecture that effectively handles the time-series data for rainfall prediction is described. This network has inputs as A_1,....A_t, hidden statesB_1,.....B_t, along with the gates C_t, D_t, E_t and the outputs F_1,....F_t. The future is predicted using the past states associated with the neighbors and the inputs that are assisted by the two operators, namely convolutional operator, which is represented as (•) and the Hadamard product, that is represented as (*). Effective prediction is provided by organizing the ConvLSTM network into forecasting and encoding layers, especially when we employ a large transitional kernel. The LSTM network consists of memory units that have cells and gates. The gates and the memory cells control the information flow. The forecast is assured based on the spatiotemporal sequences of ConvLSTM. The new input is updated in the state of the memory cell of the ConvLSTM, the unnecessary contents are forgotten, and the outputs are obtained. The input gate and output of the memory unit are computed as follows: Equation (1) describes the output at the input gate.

$$C_t = \gamma(\beta_C^A \bullet A_t + \beta_C^B \bullet B_{t-1} + \beta_C^F * F_{t-1} + \sigma^C) \tag{1}$$

where the input vector is A_t, the gate activation function is represented as γ, β_C^F is the weight among the input layer and the cell output then we have the weight among the input layer and the memory output layer that is given as β_C^B, F_{t-1} and B_{t-1} are the output of the previous memory unit and cell, respectively, β_C^A is considered as the weight among the input gate and the input layer the bias of the input layer is given as σ^C, * and • are the multiplication operator which is considered element-wise and the convolutional operator, respectively. Forget gate Dt's result is expressed as Equation (2).

$$D_t = \gamma(\beta_D^A \bullet A_t + \beta_D^B \bullet B_{t-1} + \beta_D^F * F_{t-1} + \beta^D) \tag{2}$$

where the weight amongst the forget gate mode and the input layer is β_D^A, weight between the cell and the output gate is β_D^F, the weight between the memory unit of the earlier layer and the output gate is β_D^B, and the bias of the forget gate is β^D. The output at the output gate is given by Equation (3).

$$E_t = \gamma(\beta_E^A \bullet F_t + \beta_E^B \bullet B_{t-1} + \beta_E^F * F_t + \sigma^E) \tag{3}$$

where β_E^A, β_E^B, β_E^F are the weights that link theinput layer present and the output gate, the memory unit and the output gate, and the cell and the output gate, respectively. σ^E is the bias at the output gate. The activation function of the weights is determined as the output of the temporary cell and is expressed as Equation (4).

$$\tilde{F}_t = tanH(\beta_H^A * I_t + \beta_H^B * B_{t-1} + \sigma^H) \tag{4}$$

where β_H^A is the weight among the cell and the input layer, β_H^B is considered as the weight among the cell and the memory unit, and σ^H is the bias at the cell. The sum of the difference between the memory unit of the earlier layer and the current layer and the temporary cell state is the output of the cell. The output is given by Equation (5) and Equation (6).

$$F_t = R_H * F_{t-1} + C_t * \tilde{F}_t \tag{5}$$

$$XF_t = XD_t * XF_{t-1} + XC_t * tanH(\beta_H^A * XA_t + \beta_H^B * XB_{t-1} + \sigma^H) \tag{6}$$

The memory unit's output is given by Equation (7).

$$B_t = E_t * tanH(F_t) \tag{7}$$

where E_t is the output gate and B_t is represented as the memory block output. The output layer's output is given as Equation (8).

$$P_t = \psi(\beta_P^B . B_t + \sigma^P) \tag{8}$$

where σ^P is the bias of the output layer, P_t is considered as the output vector, β_P^B is the weight between the memory unit and the output layer. The bias and the weight of the ConvLSTM are given by $\beta \in \{\beta_P^B, \beta_H^A, \beta_H^B, \beta_E^A, \beta_E^B, \beta_E^F, \beta_D^A, \beta_D^B, \beta_D^F, \beta_C^A, \beta_C^B, \beta_C^F\}$ and $\sigma \in \{\sigma^H, \sigma^D, \sigma^E, \sigma^C\}$, respectively. For the final prediction, the output that is received from the LSTM's encoding layer is served into the forecasting layer. The proposed S-SGD algorithm optimally tunes the weight and the biases of ConvLSTM.

2. Training Algorithm for ConvLSTM

The weights obtained through the ConvLSTM are trained by the adaptive S-SGD algorithm, which is the hybridization of the adaptive concept in the S-SGD algorithm, whereas the S-SGD algorithm is the alteration of the available SGD algorithm using the methodology in the SSA algorithm. The modification of the SGD algorithm with SSA helps in enhancing the ideal universal convergence capability of the algorithm [52]. The algorithmic processes of the proposed adaptive S-SGD algorithm are given as follows:

Process a: Initialization Step: At the initial stage, we have to initialize the weights which are represented by the solution vector, $k(t)$. At a certain time, t, $kd(t)$; $(1<=d<=e)$ is the representation of the solution of the algorithm

Process b: Objective Function Evaluation: The second step is where the objective function is evaluated. Here, the classifier is trained for getting the optimal solution. The optimal function is given by Equation (9).

$$Min(k) = \frac{V}{2}\|k\|^2 + fn(i_{m_t}.j_{m_t}) \tag{9}$$

The minimum value of the objective function is selected as the optimal solution.

Process c: Updating the weights using the S-SGD algorithm: The proposed algorithm is obtained by adapting the SGD algorithm along with SSA. The proposed algorithm updates the weights by altering the S-SGD algorithm with the adaptive concept. The SGD is mathematically expressed Equation (10).

$$k_d(t) = \left(\frac{t}{t-1}\right)[k_d(t+1) - i_{m_t}.j_{m_t}] \tag{10}$$

Where i_{m_t} the feature is vector and j_{m_t} is the m^{th} training sample. The weights at iteration$(t+1)$ are given by k_d $(t+1)$ and k_d (t), respectively. Based on the training input and the weights of the previous iteration, the standard update equation is computed. The chosen sample will have a target at a time t and is represented as m_q and i_{m_t}, j_{m_t} are the m^{th} training samples. Among the training data, the randomly chosen training sample is given by (i_{m_t}, j_{m_t}). The SSA update equation is given by Equation (11).

$$k_d(t+1) = \frac{1}{2}[k_d(t) + k_{d-1}(t)] \tag{11}$$

Where k_d $(t+1)$ is the d^{th} salp position at iteration$(t+1)$ is the iteration. The SGD is modified by replacing the updated equation of SSA in the SGD, which is given by Equation (12).

$$k_d(t+1) = \frac{2(t-1)}{t-2}\{\frac{1}{2} \times k_{d-1}(t) - \frac{1}{2} \times \left(\frac{t}{t-1}\right) \times i_{m_t}.j_{m_t}\} \tag{12}$$

where k_d $(t+1)$ is the newly updated weight, k_{d-1} (t) is considered as the weight at each iteration which is evolved from the previous iteration, and (i_{m_t}, j_{m_t}) is the sample of training. The classifier is trained for articulating the optimal weights using the Equation (12). For adaptive prediction of the optimal weights, the adaptive concept is included in Equation (13).

$$k_d(t+1) = \frac{t-1}{t-2}\left(k_{d-1}(t) - \frac{t}{t-1} \times i_{m_t}.j_{m_t}\right) \tag{13}$$

Here, as Equation (13) depends on iteration; it can be considered as an evolutionary factor that can be taken from PSO. The Equation (13) then becomes Equation (14).

$$k_d(t+1) = f(k_{d-1}(t) - \frac{t}{t-1} \times i_{m_t}.j_{m_t} \tag{14}$$

Where $f = \frac{v_p - v_{min}}{vmin_{max} \in [0,1]}$. From Equation (14), the finest result is selected based on the objective function that is minimum, and the best solution is generated centered on the objective function of the preceding iteration and the training sample (Equation (15) and Equation (16)).

$$v_m = \frac{1}{2-1}\sum_{d=1}^{2}\sqrt{\sum_{g=1}^{C}\left(k_d^g(t) - k_{d-1}^g(t)\right)^2} \tag{15}$$

$$v_m = \sum_{d=1}^{2}\sqrt{\sum_{g=1}^{C}\left(k_d^g(t) - k_{d-1}^g(t)\right)^2} \tag{16}$$

Process d: Termination: Steps b and c are repetitive until the iteration reaches its maximum number.

An example of the pseudo code for the proposed adaptive S-SGD algorithm is shown in Algorithm 1, with the goal of deriving optimal weights via ConvLSTM network training.

Algorithm 1: Adaptive S-SGD algorithm

INPUT: Solution vector, kd (t), (1 ≤ t ≤ q)

OUTPUT: Optimal weights, kd (t + 1).

Begin

Initialization

Population Initialization is done

Evaluation of Objective Function

Train the classifier using optimal function in Equation 9

Update the weights

Modify the S-SGD with adaptive concept as in Equation 10

SSA update as in Equation 11

Modify SGD by substituting update equation of SSA in SGD as in Equation 12

Adaptive prediction of optimal weights is included as in Equation 13

Take the evolutionary factor from PSO as in Equation 14

Best solution is generated on the objective function of the preceding iteration and the sample training data

Repeat the process

End

B. MapReduce Framework Along With Deep Learning Approach for Rainfall Prediction

The forecast of rainfall is one among the vital part in agriculture development and planning. Most rainfall prediction models utilizing weather data have failed to deal with the available massive amount of data that is called as big data [14]. As an example of huge data, consider the weather data, which can be time-series data. The MapReduce framework can solve the problems associated with big data, reducing the computational complexity and providing parallel computing. The input to the MapReduce framework is the weather data that uses the adaptive S-SGD-based ConvLSTM network and the map and reduce functions for an active rainfall prediction process. Using the suggested adaptive S-SGD algorithm, the weights of a ConvLSTM network are trained. This algorithm modifies the adaptive notion found in the S-SGD algorithm. Various delays are applied to the outputs of the individual mappers to train them. Finally, the output of the mapper is concatenated and provided as input to the reduction, which produces the final forecast. Fig. 2 depicts the suggested method for rainfall forecasting. Using the MapReduce framework, the input meteorological data is considered to be F and is utilised to predict precipitation.

1. Rainfall Prediction Based on the MapReduce Framework

The visualization is improved and the MapReduce framework provides an efficient prediction of rainfall. The framework's processing power is reduced by the given MapReduce framework by storing and distributing the datasets through a large number of servers. The ConvLSTM is trained by passing the weather data into the individual mappers. The input data is mapped using the mapper and reducer functions of MapReduce programming. These two functions of the framework based on the MapReduce model utilizes the adaptive S-SGD-based ConvLSTM network. Weather data, which acts as the input is processed using the number of mappers available in the mapper module. The mapper's output is used with intermediate data to train the reducer for the final prediction.

Mapper Phase: The first module, entitled mapper, is operated using the adaptive S-SGD algorithm that has been proposed. Consider the availability of a total of x mappers that are denoted as Equation (17).

$$Q = \{Q_1, Q_2, \ldots, Q_n, \ldots, Q_x\} \tag{17}$$

Where Q_n is the n^{th} mapper. The input weather data which has various delays are trained using the ConvLSTM in the individual mappers. For example, mapper-1 with the ConvLSTM is trained using $F(b-[D+1])$ to yield the predicted output, $F(b+w)$. In the same way, mapper-2 is trained using $F(b-[D+2])$ to give the predicted output as $F(b+w-1)$. The weather data, $F(b)$, is used for training the x^{th} mapper for providing the predicted output of $F(b+1)$. The prediction is performed by the individual mapper considering the previous records with a delay of [D + 1], [D + 2], etc. The output that is predicted at the mapper is denoted as,

$$\tilde{F}_{x+1}, \ldots, \tilde{F}_{x+wt} = \underset{F_{x+1},\ldots,F_{x+wt}}{argmax}\ \omega\left(F_{x+1}, \ldots, F_{x+wt} | \tilde{F}_{wt-D+1}, \tilde{F}_{wt-D+2}, \ldots, \tilde{F}_{wt}\right) \tag{18}$$

$$\tilde{F}_{x+1}, \ldots, \tilde{F}_{x+wt} \approx \underset{F_{x+1},\ldots,F_{x+wt}}{argmax}\ \omega\left(F_{x+1}, \ldots, F_{x+wt} | R_{encode}\left(\tilde{F}_{x-D+1}, \tilde{F}_{x-D+2}, \ldots, \tilde{F}_{x}\right)\right) \tag{19}$$

$$\tilde{F}_{x+1}, \ldots, \tilde{F}_{x+wt} \approx \eta_{forecast}\,\omega\left(R_{encode}\left(\tilde{F}_{x-D+1}, \tilde{F}_{x-D+2}, \ldots, \tilde{F}_{x}\right)\right) \tag{20}$$

The mapper output trains the inbuilt function with ConvLSTM called reducers.

Reducer phase: ConvLSTM performs the final rainfall prediction

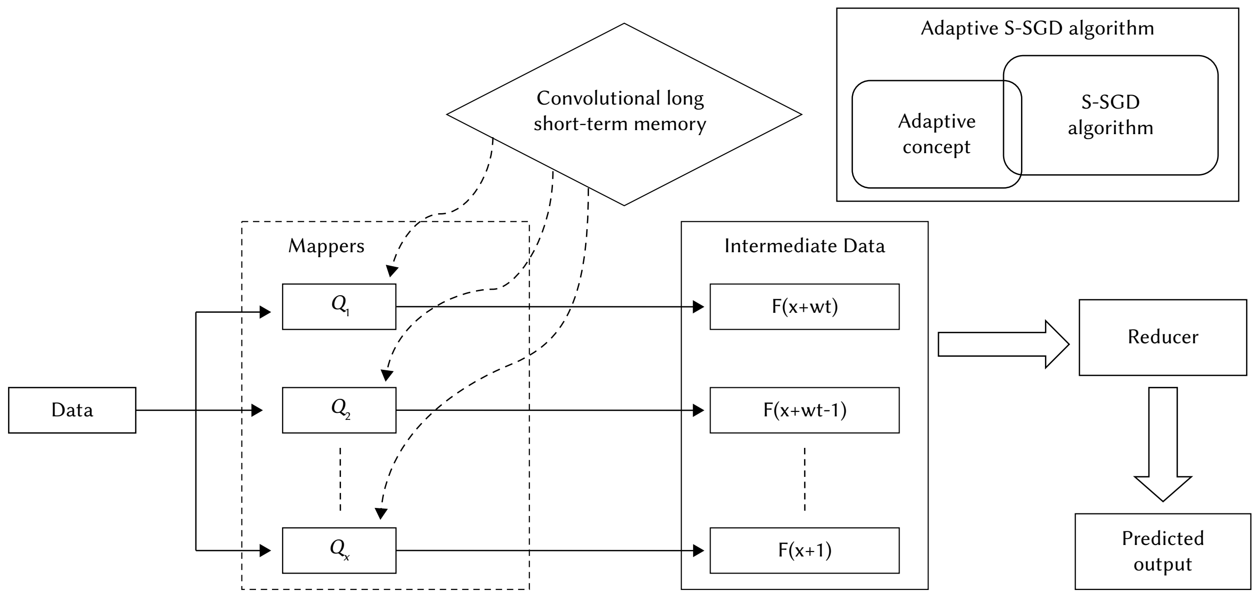

Fig. 2. Proposed rainfall prediction model's Block diagram.

with the reduce function. Using the suggested adaptive S-SGD technique, the ConvLSTM is optimally tuned during the reducer phase. The data input at the reducer is represented by Equation (21).

$$F^{inter} = \{F(b+w), F(b+w-1), \ldots, F(b+1)\} \tag{21}$$

In order to get the final prediction, the intermediate data (F^{inter}) trains the reducer. The expected result is $F(b+1)$.

Testing phase: The testing phase is one of the critical phases in the process. During the testing step, the concatenated output is obtained by feeding test data to the mappers with varying delays. The reducer of the MapReduce framework then generates the precisely predicted results.

III. Results and Discussion

This part discusses the findings obtained using the adaptive S-SGD-based ConvLSTM algorithm suggested in the previous section. To demonstrate the effectiveness of the suggested method, a comparison with existing methodologies has been conducted.

A. Experimental Setup

The recommended method was implemented in MATLAB software, and the rainfall forecast dataset was analysed [28]. The dataset contains subdivision-specific precipitation data from 1901 to 2015 spanning 115 years. The column-by-column data are presented as follows: The first twelve columns contain precipitation data from January to December. The following column has the annual precipitation data, followed by four columns containing quarterly precipitation data: JF (January and February), MAM (March, April, and May), JJAS (June, July, August, and September), and OND (October, November and December). The dataset was obtained from both data.gov.in and the Indian Meteorological Department in Pune.

These datasets were obtained via India's Open Government Data website. The dataset contains monthly rainfall information for Tamil Nadu districts. This dataset has been subdivided into three subsets containing information on annual, monthly, and quarterly precipitation.

In dataset 1, monthly rainfall series data were extracted from the dataset, including India's rainfall data. In dataset 2, annual rainfall series data were extracted from the dataset, including India's rainfall data. In dataset 3, quarterly rainfall series data were extracted from the dataset, including India's rainfall data. The dataset 4 comprises rainfall data for Tamilnadu, as well as a sequence of rainfall data by month. The dataset 5 provides rainfall data for Tamilnadu that is organised by year, and the dataset 6 contains rainfall data for Tamilnadu that is organised by quarter.

Deep analysis was performed using these six datasets, and the results were compared based on the performance metrics.

B. Performance Metrics

The proposed adaptive S-SGD-based ConvLSTM method was analyzed using the performance metrics, such as the mean square error (MSE) and the percentage root mean square difference (PRD).

MSE: MSE is the mean square difference between the expected output and estimated output. The value of MSE should be small if the method is efficient. MSE is computed as follows Equation (22):

$$MSE = \frac{1}{s}\sum_{l=1}^{s}(R_l - R)^2 \tag{22}$$

where S is the total number of samples, R_i is the estimated output, and R is the target output.

PRD: PRD is used to assess how trustworthy a certain approach is in producing precise results. It is formulated as Equation (23).

$$PRD = \sqrt{\frac{\sum_{l=1}^{s}(R_l - R)^2}{\sum_{l=1}^{s}(R_l)^2}} \times 100 \tag{23}$$

The proposed adaptive S-SGD based ConvLSTM method was compared with the existing methods, namely, S-SGD-based ConvLSTM, ConvLSTM, and CLR. This section presents the results of a comparative investigation of different rainfall prediction systems, wherein the MSE and PRD performance metrics were calculated using the six datasets.

Using dataset 1: The comparative results obtained from the various rainfall prediction methods for different training data size using dataset 1 are shown in Fig. 3 and Fig. 4.

The MSE-based analysis is shown in Fig. 3. For a training data size of 0.8, the MSE produced by the proposed adaptive S-SGD based ConvLSTM method, the existing S-SGD based ConvLSTM, and the CLR are 0.00851, 0.00871, 0.01887, and 0.00871, respectively. When compared to other methods currently in use, it is clear that the MSE value of the suggested method is the lowest.

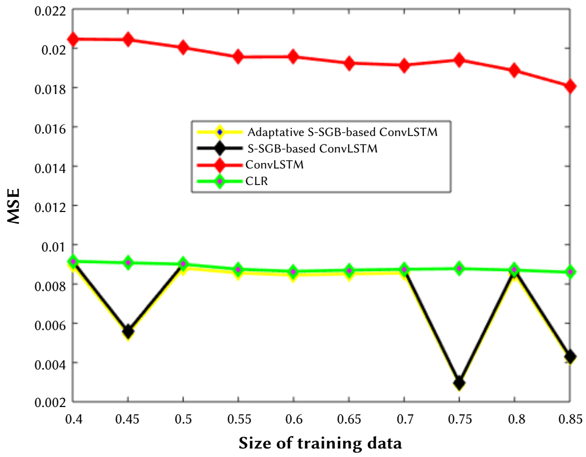

Fig. 3. MSE - Analysis using dataset 1.

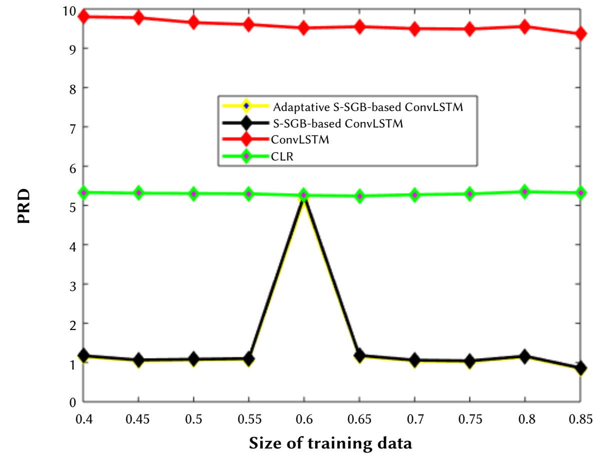

Fig. 4. PRD - Analysis using dataset 1.

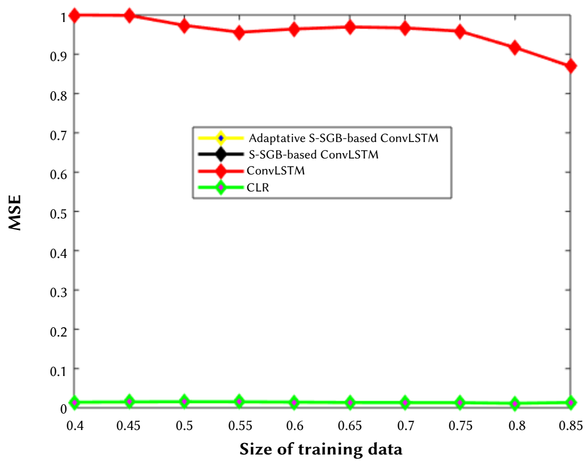

Fig. 5. MSE - Analysis using dataset 2.

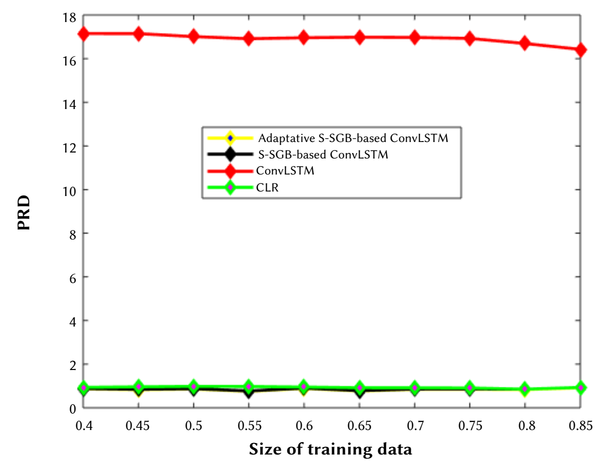

Fig. 6. PRD - Analysis using dataset 2.

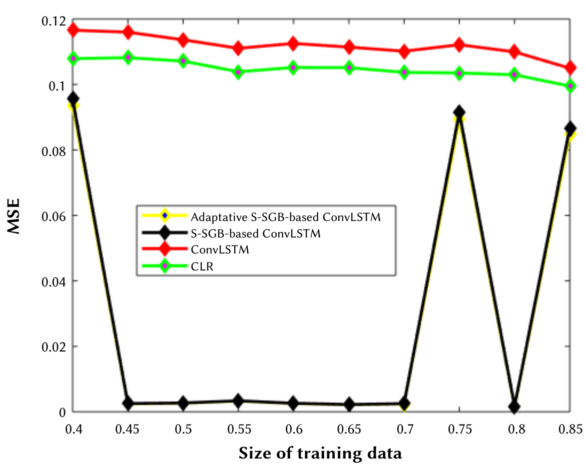

Fig. 7. MSE - Analysis using dataset 3.

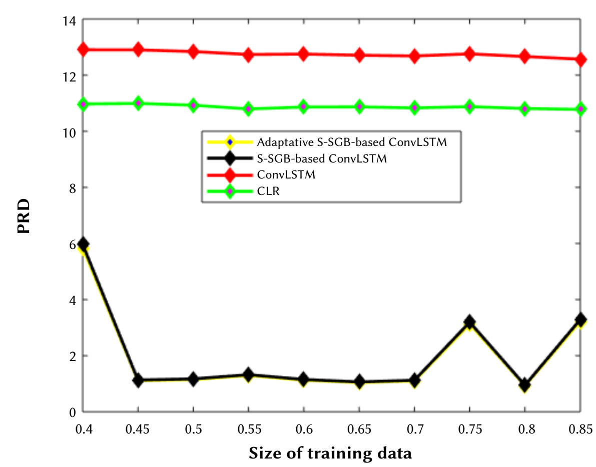

Fig. 8. PRD - Analysis using dataset 3.

Fig. 4 shows the comparative analysis based on PRD. Considering the training data size as 0.8, the PRD obtained by the proposed adaptive S-SGD based ConvLSTM and the existing S-SGD-based ConvLSTM, ConvLSTM, and CLR is 1.1377, 1.1633, 9.5547, and 5.3480, respectively.

Using dataset 2: Fig. 5 and Fig. 6 show the comparative results obtained from the various rainfall prediction methods for different sizes of training data using dataset 2. Prediction methods are assessed based on their MSE, as illustrated in Fig. 5. For a training data size of 0.8, the adaptive SSGD-based ConvLSTM achieves MSE values of 0.0112, 0.0115, 0.9169, and 0.0115, respectively.

The analysis of PRD-based prediction methods is presented in Fig. 6. For instance, at a training data size of 0.8, the proposed adaptive S-SGD-based ConvLSTM, the existing S-SGD-based ConvLSTM, and the ConvLSTM yield PRD values of 0.8340, 0.8527, 16.6927, and 0.8527, respectively. In comparison to other approaches, the suggested method demonstrates the lowest MSE and PRD values.

Using dataset 3: The comparative results obtained from the various rainfall prediction methods for different training data size using

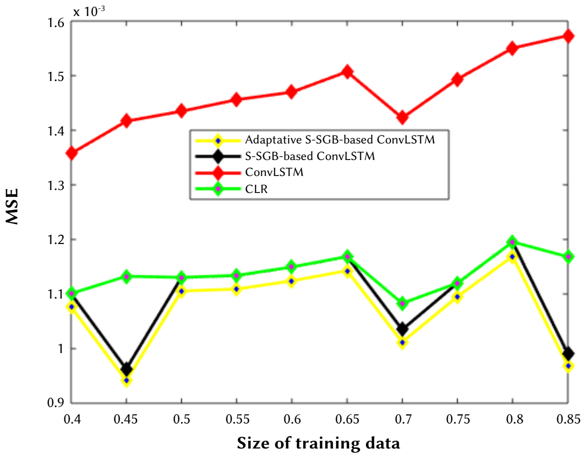

Fig. 9. MSE - Analysis using dataset 4.

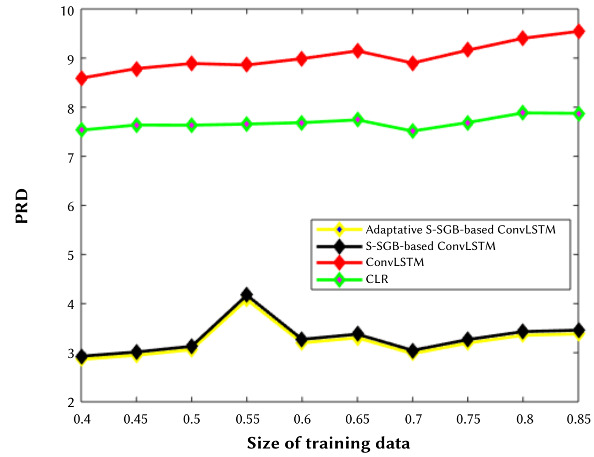

Fig. 10. PRD - Analysis using dataset 4.

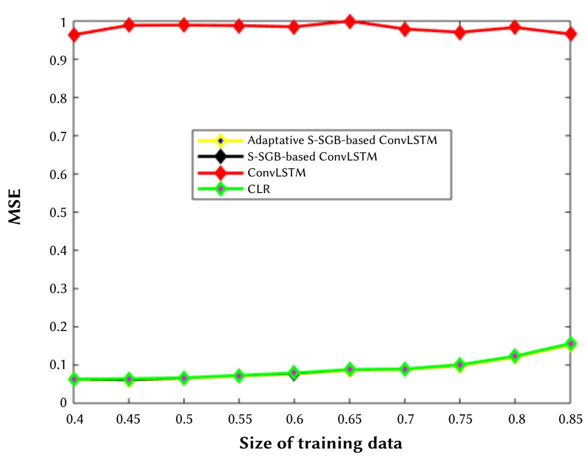

Fig. 11. MSE – Analysis using dataset 5.

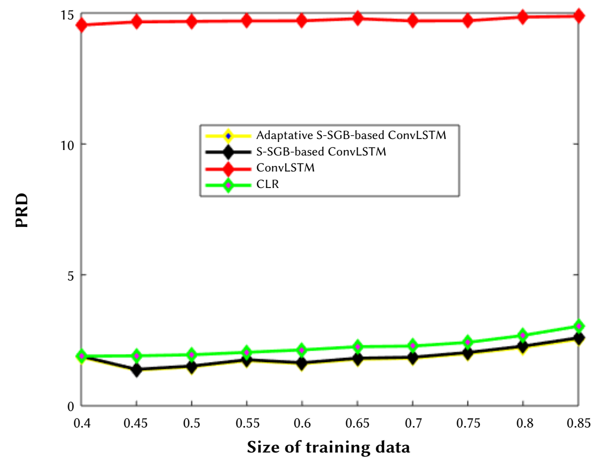

Fig. 12. PRD – Analysis using dataset 5 – PRD.

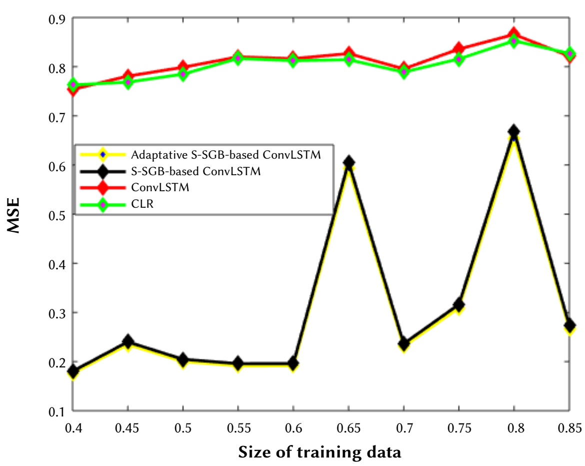

Fig. 13. MSE – Analysis using dataset 6.

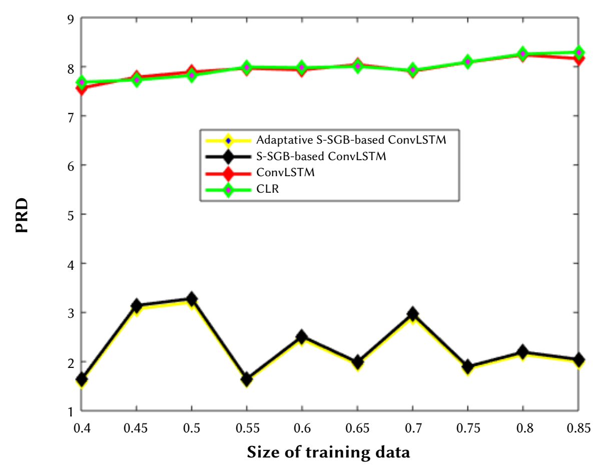

Fig. 14. PRD – Analysis using dataset 6.

dataset 3 are shown in Fig. 7 and Fig. 8.

Fig. 7 represents the analysis based on MSE. When the training data size is 0.85, the MSE obtained by the proposed adaptive S-SGD based ConvLSTM, and the existing S-SGD-based ConvLSTM, ConvLSTM, and CLR is 0.0848, 0.0867, 0.1050, and 0.0995, respectively. From the values, it is clear that the MSE value of the proposed method is the lowest compared to those corresponding to the other existing methods.

Fig. 8 depicts the comparative analysis based on PRD. Considering the training data size as 0.85, the PRD corresponding to the proposed adaptive S-SGD based ConvLSTM and the existing S-SGD-based ConvLSTM, ConvLSTM, and CLR is 3.2199, 3.2923, 12.5674, and 10.7774, respectively.

Using dataset 4: Fig. 9 and Fig. 10 show the comparative results obtained from the various rainfall prediction methods for different size of training data using dataset 4.

Fig. 9 depicts the analysis of the prediction methods based on MSE. MSE obtained by the proposed adaptive S-SGD-based ConvLSTM and the existing S-SGD-based ConvLSTM, ConvLSTM, and CLR for a training data size of 0.85 is 0.00097, 0.00099, 0.00157, and 0.00117, respectively.

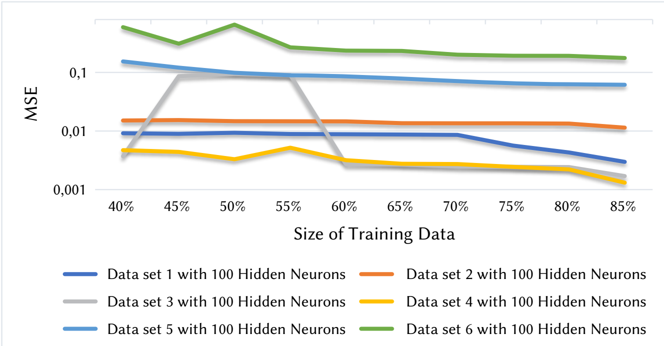

Fig. 15. Overall MSE comparison of the complete six datasets.

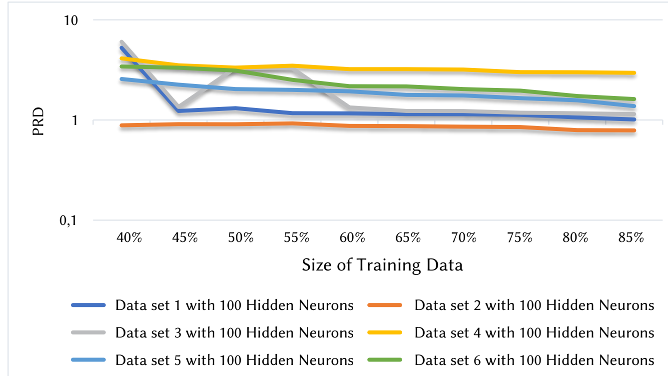

Fig. 16. Overall PRD comparison of the complete six datasets.

Fig. 10 depicts the analysis of the prediction methods based on PRD. PRD corresponding to the proposed adaptive S-SGD-based ConvLSTM and the existing S-SGD-based ConvLSTM, ConvLSTM, and CLR for a training data size of 0.85 is 3.3828, 3.4589, 9.5439, and 7.8748, respectively. The proposed method exhibits the lowest MSE and PRD values compared to the other existing methods.

Using dataset 5: The comparative analysis of the various rainfall prediction methods for different training data size using dataset 5 is shown in Fig. 11 and Fig. 12.

Fig. 11 depicts the analysis based on MSE. Considering the training data size to be 0.85, the MSE obtained by the proposed adaptive S-SGD-based ConvLSTM and the existing S-SGD-based ConvLSTM, ConvLSTM, and CLR is 0.15259, 0.15603, 0.96569, and 0.15604, respectively. The analysis shows that the MSE value of the proposed method is the lowest compared to the other existing methods.

Fig. 12 shows the comparative analysis based on PRD. Considering the training data size as 0.85, the PRD obtained by the proposed adaptive S-SGD-based ConvLSTM and the existing S-SGD-based ConvLSTM, ConvLSTM, and CLR is 2.5377, 2.5948, 14.8740, and 3.0397, respectively.

Using dataset 6: Fig. 13 and Fig. 14 show the comparative analysis of the rainfall prediction methods for different size of training data using dataset 6.

Fig. 13 depicts the analysis of the prediction methods based on MSE. MSE values corresponding to the proposed adaptive S-SGD-based ConvLSTM and the existing S-SGD-based ConvLSTM, ConvLSTM, and CLR for a training data size of 0.85 are 0.2673, 0.2733, 0.8215, and 0.8270, respectively.

Fig. 14 depicts the analysis of the prediction methods based on PRD. The PRD values corresponding to the proposed adaptive S-SGD-based ConvLSTM and the existing S-SGD-based ConvLSTM, ConvLSTM, and CLR for a training data size of 0.85 are 1.9996, 2.0446, 8.1656, and 8.2950, respectively. The proposed method exhibits the lowest MSE and PRD values compared to the other existing methods.

The performance of the proposed Adaptive SGD-based ConvLSTM as well as existing methods such as convLSTM CLR and S-SGD based ConvLSTM is evaluated using performance measures such as MSE and PRD. According to the overall performance study of adaptive S-SGD based ConvLSTM in terms of MSE for the 6 datasets, the adaptive S-SGD based model performs best for Tamilnadu monthly rainfall prediction, followed by India's quarterly rainfall prediction. According to the overall performance study of adaptive S-SGD based ConvLSTM in terms of PRD for the 6 datasets, the adaptive S-SGD based model performs best for India's yearly rainfall forecast, followed by India's monthly rainfall prediction.

The overall performance analysis of adaptive S-SGD based ConvLSTM in terms of MSE for the 6 datasets with 100 hidden neurons is observed, and it is stated that the adaptive S-SGD based model performs well for monthly rainfall prediction of Tamilnadu, followed by the quarterly rainfall prediction of India. The next priority is given to the monthly and yearly prediction of rainfall in India, followed by Tamilnadu's yearly and quarterly rainfall prediction. It has been shown in Fig. 15 and Fig. 16.

Some of the major findings of the proposed method for rainfall prediction in agriculture are illustrated below.

- The simulation results of the proposed Adaptive SGD-based ConvLSTM and SGD-based ConvLSTM are compared with the existing techniques, like ConvLSTM and CLR.
- The proposed Adaptive SGD-based ConvLSTM provides MSE as 0.00292 and PRD value as 0.84501.
- The proposed SGD-based ConvLSTM has values of 0.00298 and 0.86402 as MSE and PRD, respectively.
- Among all the comparative methods, the proposed Adaptive SGD-based ConvLSTM has improved performance for MSE and PRD.
- Thus, it is clearly shown that the proposed Adaptive SGD-based ConvLSTM considerably increases the system performance.
- The proposed algorithms can efficiently predict the monthly, quarterly, and yearly rainfall.

The main limitations of this study and the future suggestions are as follows:

- This study can be extended to discover other interesting patterns in the time series data analysis using optimization algorithms.
- In this paper, we have not considered rainfall prediction in a short span.
- The future studies may focus on getting the prediction accuracy without directly using the processed data for analysis.
- Other datasets need to be adopted to check the validity of schemes in real-time.

IV. Conclusion

As part of this effort, an adaptive SSA-based ConvLSTM system was created to reliably predict precipitation from a given set of meteorological inputs. For the weather forecast, we took in dynamically updated time series data processed with the MapReduce framework. Implementing the proposed adaptive S-SGD-based ConvLSTM model in the MapReduce framework proved highly helpful in dealing with the big data problems. The mapper and reducer components of this architecture are helpful in estimating precipitation. The suggested adaptive S-SGD-based ConvLSTM was fed the input data, and its weights were fine-tuned using a MapReduce framework. The suggested rainfall prediction model was evaluated using six datasets taken from the Rainfall Prediction database. The MSE and PRD evaluation metrics were used for the performance study of the proposed approach. The proposed technique was shown to have better prediction accuracy, with an MSE and PRD of 0.0042 and 0.8450, respectively. To improve the accuracy of this technique, a hybrid fusion model for forecasting precipitation should be created. However, only two measures of efficiency were considered in this paper. Accuracy, Precision, F-measure, and Recall are just a few examples of future performance metrics that will be analysed.

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