A SURVEY OF RAINFALL PREDICTION USING DEEP LEARNING

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***Abstract*— Prediction of rainfall is a difficult task because of the high volatility and complicated nature of the atmospheric data. Recently, various deep learning methods were successfully applied to forecast rainfall. We survey papers that employ deep learning techniques to predict rainfall using meteorological data. The papers are examined in terms of the deep learning methods applied, location of the study area, types of metrics and software used for implementing the model and, year-wise publication of the papers. From the surveyed papers, we found that deep learning methods can be applied successfully for rainfall prediction and they are found to be superior than the traditional machine learning methods and shallow neural network models. We also provide future directions for research in the area of rainfall prediction.**

Keywords*— Rainfall prediction, Artificial neural network, Machine Learning, Deep Learning

I. Introduction

Accurate rainfall prediction is necessary because of its impact in the fields of agriculture, transportation, water supply, renewable energy management and, various activities of human beings. As rainfall prediction depends on multiple environmental factors, it is a challenging task [1]. Rainfall prediction methods can be categorized into physical methods, statistical methods, and machine learning techniques. Physical methods are models that are implemented using numerical weather prediction. Physical methods have a drawback because they require large computational resources and large data requirements for calibrating the model. On the other hand, the statistical model aims to uncover the mathematical relationship between online time-series problems. Autoregressive Integrated Moving Average (ARIMA), Multiple Regression and, Linear Regression (LR) are commonly used in statistical modelling. For many years researchers have applied machine learning models for prediction of rainfall [1]–[5]. Support Vector Machine (SVM) and neural network model such as Artificial Neural Network (ANN) are commonly used machine learning models for rainfall prediction. A type of Machine learning model called Deep learning model implement deep structure in its architecture. It is a composition of several processing layers to learn the data representations using multiple level of abstraction [6]. Deep learning methods are employed successfully in the area of forecasting, classification problem, image and natural language processing, speech recognition, object detection, etc. [7]–[14].

Rainfall forecasting has been an active area in literature. Several survey papers that applied machine learning models in forecasting rainfall and other weather parameters have been published. [15] presented an overview of various computational intelligence tools for weather prediction aiming on how the neural networks can predict various weather phenomena such as temperature, tidal level, rainfall, and flood. A survey of satellite-based rainfall prediction technique was presented by [18]. [19] presented a study of statistical methods and data mining techniques for the prediction of rainfall. [20] provided a critical study of papers published from 2013 to 2017 for rainfall prediction based on data mining techniques. Recently, there is an increasing interest in the use of deep learning for rainfall prediction, however there is a lack of survey papers that focused on rainfall prediction using deep learning methods. Thus, the purpose of this paper is to fill this gap and study the papers that used deep learning methods for the prediction of rainfall. We classify the papers based on the nature of data used to train and test the deep learning models. We study the types of metrics and software used, yearly trends of the papers published, the location of the case study, and the type of deep learning methods applied for the prediction. Furthermore, we also discuss the performance of deep learning models compared to machine learning models and the potential future research directions.

This paper is organized as follows. Section II discusses the methodology for conducting the survey. In section III, we summarized the deep learning methods applied for the prediction of rainfall. Section IV presents the result and discussion and in section V we mention the future directions. Finally, the conclusion is given in section VI.

II. Methodology

The process of this survey consists of the following steps: (a) Collection of papers with a focus on the use of deep learning methods for rainfall prediction (b) detailed survey and analysis of the collected papers.

In the first step, well-known digital libraries such as ScienceDirect, IEEE Xplore, Springer, and Google Scholar were searched for Journal articles and Conference paper using the combination of keywords given below: -

["deep learning" OR "machine learning"] AND ["rainfall" OR "precipitation] AND ["forecasting" OR "prediction"]

Using the search criteria given above, 246 papers were collected. The collected papers were screened and 45 papers were selected for the detailed study after applying the following inclusion criteria: -

1) *Papers published from January 2015 to June 2020*
2) *Papers from peer-reviewed journals and conferences.*
3) *Papers that predict rainfall*
4) *Papers that used deep learning methods*

In the second step, 45 papers selected from the above steps were studied in detail. The following research questions were considered while surveying the selected papers:

1) Which deep learning methods were used for rainfall predictions?

2) Which metrics were used for evaluating the performance of the method?

3) What are the sources of datasets used in the papers?

4) What parameters are used for training?

5) Does deep learning provide better prediction compared to other methods?

III. Applications of Deep Learning in Rainfall prediction

In this paper, we categorized the rainfall forecasting task based on the type of data used for training and evaluation of the models. We classify the type of data as weather parameter data, radar image data, and satellite image data. Out of 45 papers surveyed, 26 papers used weather parameters, 13 papers used radar images, and 6 papers used satellite images for training and testing the models.

A. Rainfall prediction using weather parameters

In this section, we present the papers that used weather parameters collected using Meteorological Observation Stations such as surface observation, upper air observation, and ocean observation. *Table I* summarized the papers that used weather parameters for the prediction of rainfall. The deep learning methods used, compared methods, framework used, country, temporal resolution, and metrics for evaluating the models were also given in the table.

(Saha et al., 2016, 2017, 2021) identified the predictors for early-late Indian summer monsoon, monsoon in the homogeneous regions of India, and aggregate Indian summer monsoon using a deep learning method called stacked autoencoder. The identified predictors are used for the long-term forecast of monsoon using machine learning models such as Regression Tree with Bagging algorithm (RegTreeB) and Decision Tree with Bagging algorithm (DecTreeB). The proposed prediction models are compared with Indian Meteorological Department (IMD) monsoon prediction models. Results of the study showed that the proposed prediction models with the identified monsoon predictors outperformed the compared IMD models.

[24] used a deep learning technique called Denoising Autoencoder (DAE) and a Multilayer Perceptron (MLP) for predicting the next day's rainfall. The autoencoder extract non-linear features from the input meteorological data and the MLP network is used for classification and prediction. The authors compared the proposed model with MLP, naive approach, Back Propagation network (BP), Layer Recurrent Network (LRN), Cascaded Back-Propagation (CBP), Ensemble Empirical Mode Decomposition (EEMD), and Feed-forward Neural Networks (FNN). The result showed that the proposed method achieved lower Mean Squared Error (MSE) and Root Mean Squared Error (RMSE) than the compared methods.

[25] predicted heavy rainfalls during the monsoon season (June, July, August, and September). Due to a huge set of features, Stacked Autoencoder (SAE) was used as a tool for feature reduction. The reduced features are then used for the classification of heavy rainfalls using a cost-sensitive SVM. The proposed SAE-SVM and Stacked Autoencoder Neural Network (SAE-NN) model was compared with Stacked Autoencoder - Anomaly Frequency Method (SAE-AFM), Principal Component Analysis- Support Vector Machine (PCA-SVM), and Fisher Linear Discriminant Analysis (LDA). Results showed that the proposed model is better for heavy rainfall prediction.

[26] proposed Deep Belief Network for Precipitation Forecast (DBNPF) for short-term rainfall forecasting. The authors compared the DBNPF with Radial Basis Function (RBF) neural network, SVM, ARIMA, Extreme Learning Machine (ELM), and SAE models. [27] also implemented DBNPF model for predicting rainfall in four areas of China such as Zunyi of Guizhou Province, Hezuo of Gansu Province, Jinan of Shandong Province, and Changchun of Jilin Province. In both the papers, the research results suggested that the DBNPF model is better than the other models.

Echo State Networks (ESN) and Multi-Gene Genetic Programming (MGGP) were proposed by (Ouyang and Lu, 2017) to forecast monthly rainfall. The proposed models were compared with the Support Vector Regression (SVR) method for 1-, 3- and 6-months lead time. The authors also compared the performance of Wavelet Transform (WT), Singular Spectrum Analysis (SSA), and Ensemble Empirical Mode Decomposition (EEMD) for pre-processing of data. Among the forecasting models, ESN outperformed SVR and MGGP, and SVR was better than MGGP. However, all three models were found to be suitable for monthly rainfall forecasting. Among the data pre-processing methods, WT was a good technique for forecasting short-term rainfall whereas, SSA performed better for forecasting of long-term rainfall. EEMD showed the poorest performance compared to WT and SSA. The best-performing model (SSA-ESN) can forecast rainfall up to 2 years lead time with acceptable accuracy.

[29] predicted short-term rainfall using the features collected from a network of rain gauges. Deep Convolutional Neural Network (CNN) was used for extracting features from the input data and a fully connected layer for the prediction task. The authors compared the proposed multi-task CNN method with Quantitative Precipitation Forecast (QPF), LR, MLP, AE-MLP, Long Short-Term Memory (LSTM), CNN, Multi-task MLP, and Multi-task Recurrent Neural Network (RNN). Experimental results showed that the proposed model significantly outperformed the compared models.

[30] applied deep learning model called Deep Belief Network (DBN) for precipitation forecasting. DBN was compared with SVM and SVM based on different optimization algorithms such as Particle Swarm Optimization (PSO). The time consumed by DBN was lower than the SVM methods, and it was founded that SVM methods can be used for small datasets whereas the DBN method can be used for large-scale datasets.

Very Short-Term precipitation forecasting was studied by [31] and compared the performance of Deep Neural Network (DNN) with SVM, XGBoost (XGB), Random Forest (RF), and Random Prediction (RP) methods. Among the compared methods, DNN yields the highest accuracy for rain prediction.

[32] investigated the capability of DNN to predict monthly rainfall. After testing different hidden layers and hidden nodes, the authors considered 5 hidden layers with 128 nodes in each layer for the DNN model. Based on the results, the DNN model was found to be appropriate for forecasting

monthly rainfall with a one-month lead time. The accuracy of the model was decreased when increasing the lead time.

[33] compared the performance of LSTM with MLP and Seasonal Neural Networks (SNN) for predicting rainfall. The result of the experiment suggested that LSTM was better in terms of performance than the compared methods. The authors stated that LSTM can be a promising model for estimating precipitation.

[34] applied LSTM for forecasting monthly rainfall and explores the selection of optimal time lag for the model. The LSTM model was compared with RNN and it was tested on various homogeneous regions of India. The study observed that the LSTM model outperformed the RNN model for different fitness measures and 12 to 15 antecedent rainfall events provide more valuable information.

[35] developed a deep neural network composed of convolutional layers and an LSTM network for improving Monsoon precipitation prediction. The convolutional layers were used to extract spatial features of the raw input data, which was then fed to the LSTM networks. The effectiveness of the predictors was studied and the geopotential height was found to be the most important predictor. The proposed Convolutional Long Short-Term Memory (ConvLSTM) model was compared with Quantile Mapping (QM) method, SVM, and CNN and the precipitation estimate given by the ConvLSTM network was found to have the highest performance.

[36] proposed the identification of break and active monsoon spells for the central region of the Indian subcontinent using LSTM and Sequence-to-Sequence (Seq2Seq) models. The Seq2Seq model consists of two LSTM units, a dense soft-max layer, and an attention mechanism. The authors classified each day as dry, wet, or normal day. Then the collection of classification at daily scale was used to detect the break or active monsoon spells. Daily rainfall from June to September (1948 - 2014) was considered for detection of monsoon spells. The proposed models were compared with SVM and K-Nearest Neighbor (KNN) and it was observed that both LSTM and Seq2Seq performed better than SVM and KNN. Additionally, the Seq2Seq model was found to be superior to LSTM for detecting monsoon spells.

[37] used Echo State Networks (ESN) and DeepESN to predict rainfall using meteorological data. The study was conducted in the area of Southern Taiwan. The authors compared the performance of the proposed models with Back Propagation Network (BPN) and SVR. To find the most important parameter to predict rainfall, the authors used the Principal Component Analysis (PCA) method. Rainfall, pressure, and humidity are found to be the most important parameters. The experimental result showed that the correlation coefficient for the ESN and DeepESN is greater than BPN and SVR model. It was also found that DeepESN was more accurate and has the best performance than the compared models.

[38] proposed a cascading deep learning method to classify rain/no-rain and to predict the amount of rainfall. CNN was used as a classification model to classify rain or no-rain and using the classified rain class Gated Recurrent Unit (GRU) was used to predict the amount of rainfall. Focal loss with sigmoid activation was used by the authors to prevent bias to non-rain class. The proposed cascaded model was compared with Autoregressive Integrated Moving Average (ARIMA), Autoencoder Multilayer Perceptron (AE-MLP), Multitasking Convolutional Neural Network (MT-CNN), Multitasking Gated Recurrent Unit (MT-GRU). For a single time-step, the proposed model provides a lower Root Mean Squared Error (RMSE) than the compared models. In the case of a multi-step model with a rolling mechanism to forecast the next 6-time steps, the proposed model is found to be useful but limit accuracy.

[39] proposed Intensified LSTM for the prediction of rainfall. To solve the issue of the LSTM vanishing gradient problem, the authors modified the LSTM by multiplying the input value with the sigmoid function in the input gate and the tanh function in the candidate vector. This reduced the training time of the network which in turn caused a high learning rate and reduced the losses. The proposed Intensified LSTM model was compared with Holt-Winters, Extreme Learning Machine (ELM), ARIMA, Recurrent Neural Network (RNN with Rectified Linear Unit (ReLU), RNN with Sigmoid Linear Unit (SiLU), and LSTM models. Experimental results showed that the accuracy of the proposed model outperformed the compared models.

[40] developed two LSTM based models, Wavelet Long Short-Term Memory (WLSTM) and CLSTM to forecast streamflow and rainfall. WLSTM is a hybrid model composed of LSTM and wavelet transform and CLSTM is composed of CNN and LSTM. WLSTM and CLSTM models were compared with three layers MLP and LSTM. Results showed that WLSTM and CLSTM outperformed LSTM and MLP for both stream fall and rainfall forecasting. The forecasting accuracy of LSTM was improved using the wavelet transform and convolutional layers.

[41] adopted a deep learning model called LSTM and K-Means clustering method. The data samples were first divided into four categories using the K-means clustering method followed by building the models using LSTM for the different data types. The proposed model was compared with Frequency matching, Linear regression, SVM, and DBN using RMSE and Threat Score (TS). The proposed model was found to reduce the RMSE effectively and it improved the TS of light and heavy rain.

[42] constructed and trained a deep CNN model for severe convective weather such as heavy rain, hail, convective gusts, and thunderstorms. The authors constructed two databases based on Severe Convective Weather (SCW) observations and NCEP final (FNL) analysis data. The proposed CNN model was compared with Logistic Regression (Logit Reg), Random Forest (RF), Support Vector Machine (SVM), and Multilayer Perceptron (MLP). Results showed that the deep CNN model outperformed the compared traditional machine learning algorithms in SCW forecasting over China.

ConvLSTM tuned using the Salp-Stochastic Gradient Descent (S-SGD) algorithm was proposed by [43] for the prediction of rainfall in India. S-SGD algorithm is a hybrid of Salp Swarm Algorithm (SSA) and Stochastic Gradient Descent (SGD) algorithm and they are used to select the optimal weights of the ConvLSTM model. The authors implemented the MapReduced framework to deal with a large amount of data in parallel. The performance of the model was compared with ConvLSTM, Clusterwise linear regression (CLR), MLP, and Dynamic Self-organizing Multilayer Network Inspired by the Immune Algorithm (DSMIA). It is found that the proposed model S-SGD based ConvLSTM

TABLE I. SUMMARY OF PAPERS WHICH PREDICT RAINFALL USING WEATHER PARAMETERS

Author	Methods	Comparison	Framework	Country	Resolution	Metrics
[25]	SAE-SVM, SAE-NN	SAE-AFM, PCA-SVM, Fisher LDA	-	India	Daily, 6-hours	-
[24]	DAE, MLP	MLP, Naïve, BPN, LRN, CBP, EEMD, FFNN	Theano	Colombia	Daily	MSE, RMSE
[66]	SAE, RegTreeB	IMD Models	-	India	Monthly	-
[21]	Sparse AE, RegTreeB, DecTreeB	IMD Models	-	India	Monthly	MAE
[28]	ESN, MGGP	SVR	MATLAB	China	Monthly	RMSE, MAE, NSE
[29]	MT-CNN	LR, MLP, AE-MLP, LSTM, CNN, MT-MLP, MT-RNN, ECMWF	PAI	Colombia China	Daily	MSE, CSI, CORR
[22]	SAE, RegTreeB	IMD Models	MATLAB	India	Monthly	MAE
[26]	DBNPF	RBF, SVM, ARIMA, ELM, Sparse AE	MATLAB	China	Daily	MAE, RMSE
[33]	LSTM	MLP, SNN	MATLAB, Python	Vietnam	Monthly	CORR, R, RMSE, MAE
[30]	DBN	SVM, PSO-SVM	Theano	China	3 hours	-
[32]	DNN	-	Tensorflow	Thailand	Monthly	SEF
[31]	DNN	SVM, XGB, RF, RP	Chainer	Japan	10 minutes	recall, F-score
[27]	DBNPF	SVM, RBF, ARIMA, ELM	MATLAB	China		MAE, RMSE
[34]	LSTM	RNN	Keras	India	Monthly	RMSE, CORR, NSE, MAE
[67]	CNN-GRU	ARIMA, AE-MLP, CNN, MT-GRU,CNN-GRU		Thailand	Hourly	F1 score,RMSE
[43]	S-SGD-based convLSTM	convLSTM, CLR, MLP, DSMIA	MapReduce framework MATLAB	India	Monthly, Quarterly, Yearly	RMSE, NSE, R2
[35]	ConvLSTM	QM, SVM, CNN	Tensorflow	China	Daily	NSE, RB
[40]	WLSTM, CLSTM	MLP, LSTM		China	Monthly	RMSE, Accuracy
[39]	Intensified LSTM	Holt–Winters,ELM, ARIMA RNN-Relu, RNN-Silu, LSTM	Keras	India		RMSE, TS
[36]	LSTM, Seq2Seq model	SVM, K-NN		India	Daily	Precision, Recall, Accuracy, F1-score
[37]	ESN, DeepESN	BPN, SVR, ECMWF	MATLAB	Taiwan	Hourly	RMSE, NRMSE, TS CORR, POD, FAR,
[41]	LSTM	LR, SVM, DBN	Python	China		MSE, PRD
[42]	CNN	Logit Reg,RF, SVM, MLP		China	6 hours	TS,ETS, POD,FAR
[45]	MIMO-LSTM, MISO-LSTM, MIMO-TCN, MISO-TCN,	SR, SVR, RF, ARIMA, VAR, VECM, AFE, WRF-NWP	Keras		3 hours	TS, ETS, POD, FAR
[44]	Stacked LSTM	ANN, GRU	-	Australia	30 secs, 15 mins	RMSE, MAE, R2,CV,Bias
[23]	SAE, RegTreeB, DecTree	IMD Models	-	India		MAE

outperformed the compared models in terms of Percentage Root mean square Difference (PRD) and Mean Squared Error (MSE).

[44] designed a deep learning model based on a two-layer LSTM model and trained the model using a disdrometer-derived dataset. The model was then applied to improve rainfall estimation using Commercial Microwave Link (CML) data. Based on the attenuation of the transmitted electromagnetic signal as it passed through the rain, rainfall was estimated using CML networks. The authors compared the LSTM model with GRU and ANN. The results showed that GRU performed better than LSTM in terms of relative bias, whereas the LSTM model performed slightly better than GRU and much better than ANN in terms of RMSE, Mean Absolute Error (MAE), Coefficient of Determination (R^2), and Coefficient of Variation (VC).

[45] proposed LSTM and Temporal Convolutional Networks (TCN) for short-term forecasting of rainfall using 10 surface weather parameters. They compared the performance of the models with Standard Regression (SR), SVR, RF, ARIMA, Vector Auto Regression (VAR), Vector Error Correction Model (VECM), and Arbitrage of Forecasting Expert (AFE) models. Two regression models namely Multi-Input Multi-Output (MIMO) and Multi-Input Single-Output (MISO) were proposed to evaluate the proposed models. MIMO-LSTM and MISO-LSTM

outperformed the compared models and they were selected as the proposed model. Since MISO-LSTM and MIMO-LSTM do not produce much difference and due to easily handle and less time and power consumption MIMO-LSTM was selected for further analysis. Then, the author compared the MIMO-LSTM with Weather Research and Forecasting - Numerical Weather Prediction (WRF-NWP) model and found that MIMO-LSTM provides better prediction up to 12 hours.

B. *Rainfall prediction using Radar image*

To increase the spatial coverage and resolution of the data, radar images are widely used by researchers to predict rainfall. In *Table II* we summarized the papers that used radar images for the prediction of rainfall. [46] proposed convolutional LSTM (ConvLSTM) for short-term rainfall prediction. The authors extended the Fully Connected LSTM (FC-LSTM) by incorporating convolutional structures in the input-to-state and state-to-state transitions. ConvLSTM is compared against FC-LSTM and the Real-time Optical flow by Variational methods for Echoes of Radar (ROVER). The FC-LSTM does not perform very well due to the spatial correlation in the radar data. ROVER is found to give a sharper prediction, but it triggers more False alarms and is found to be less precise than ConvLSTM. The authors concluded that ConvLSTM is better in capturing the spatiotemporal correlations and it also provides better predictions than the ROVER algorithm.

[47] predicted short-term precipitation using Convolutional Long Short-Term Memory (convLSTM) using the radar data. Hyper-parameter search was performed using Spearmint to select the convolutional kernel size, the number of convolutional filters, learning rate, and momentum. The results show that the standard encoder-decoder method is more successful in Probability of Detection (POD) and Critical Success Index (CSI) and only a slight increase in false alarm over the attention model.

[48] proposed a Trajectory Gated Recurrent Unit (TrajGRU) for short-term rainfall prediction and compared its performance with Convolutional Gated Recurrent Unit (ConvGRU), Dynamic Filter Network (DFN), 2D and 3D Convolutional Neural Networks (CNNs), and two optical flow-based models (ROVER and its nonlinear variant). Due to high imbalance in the proportions of rainfall events at different rain-rate, the authors also proposed Balanced Mean Square Error (B-MSE) and Balanced Mean Absolute Error (B-MAE) for training and evaluation of the models. The experiments show that TrajGRU outperforms the compared models and training of the models using the balanced loss function performs better than training without balanced loss.

[49] explored the prediction of rainfall using a radar echo dataset by incorporating convolution operations within the vanilla recurrent neural network. The proposed Conv-RNN model was compared against Conv-LSTM and Eulerian Persistence models. The authors states that Conv-RNN can be used for learning the features of the Doppler weather radar phenomenon and lesser parameters are used compared to other hybrid approaches. Convolutions in recurrence also encode the Spatio-temporal correlations.

DeepRain- a ConvLSTM model was proposed by [50] to predict the amount of rainfall using radar observation. The prediction accuracy of the proposed method is found to be better than Linear Regression and FC-LSTM models. The result also showed that the two-stacked ConvLSTM performed more stable than the one-stacked ConvLSTM.

To enable researchers to develop, test and deploy new models significantly faster [51] studied a distributed learning approach to train a precipitation nowcasting model. In this study, a data-parallel model was implemented in which a CNN model and the training batches were replicated across multiple compute nodes. The CNN model was Fully Convolutional without dense layers. The authors implemented the model using TensorFlow/Keras and Horovod framework and the model was trained using up to 128 GPUs. Using the proposed approach, the training time for a given nowcasting model architecture was reduced from 59 hours to just about 1 hour. The result also showed that the validation loss reduced smoothly up to 24 GPUs. A noisy behavior was detected in the validation loss after increasing the number of GPUs beyond 24 which could be due to a significant reduction in the training images available for each device.

[52] proposed a Generative Adversarial ConvGRU (GA-ConvGRU) model which is a composition of two adversarial learning systems, ConvGRU-based generator, and a convolutional neural-network-based discriminator. The authors utilized a sequence of five radar echo images and predict ten radar echo maps. Results of the experiments showed that GA-ConvGRU outperformed ConvGRU and optical flow methods.

[53] compared the performance of U-Net CNN with the Optical flow model, persistence model, and NOAA's numerical one-hour High-Resolution Rapid Refresh (HRRR) for short-term precipitation prediction. The authors treated the forecasting problem as an image-to-image translation problem where n sequence of radar images was used as input to the model. The study showed that the proposed model outperformed the compared models.

[54] proposed sequence-to-sequence model called dec-seq2seq model. The dec-seq2seq model consists of dec-TrajGRU, dec-ConvGRU, and dec-ConvLSTM. The dec-seq2seq models were compared with TrajGRU, ConvGRU, and ConvLSTM and showed improvements over the compared models. Among the dec-seq2seq models, dec-TrajGRU performed better than the other models. To resolve the blurry image issue due to the impact of the loss functions such as MAE or MSE, an image quality assessment metrics Structural Similarity (SSIM) and Multi-Scale Structural Similarity (MS-SSIM) were proposed by the authors. The experimental result showed that the best loss function is combination of SSIM, MSE, and MAE and the dec-seq2seq models can tolerate high and increasing uncertainty.

To improve the accuracy of Doppler radar detection of short-term rainfall prediction, Tiny-RainNet was proposed by [55]. Tiny-RainNet consists of a combination of Bi-directional Long Short-Term Memory (BiLSTM) and CNN to extract the temporal and spatial information. The authors compared the proposed model with ConvLSTM, LSTM, FC-LSTM, and AlexNet and it was found that Tiny-RainNet had a better performance than the compared models.

[56] developed RainNet, a deep convolutional neural network for radar-based short-term precipitation forecasting. RainNet model consists of a stacked of CNN following a standard encoder-decoder structure with skip connection between its branches. Initially, RainNet predicted the precipitation for a lead time of 5 minutes and to predict a larger lead time up to 60 minutes. RainNet was applied recursively by using the previous output as the next input. The

TABLE II. SUMMARY OF PAPERS WHICH PREDICT RAINFALL USING RADAR IMAGE

Author	Methodology	Comparison	Framework	Country	Spatial Resolution	Temporal Resolution	Metrics
[46]	ConvLSTM	FC-LSTM, ROVER	Theano	-	-	-	MSE, CSI, FAR, POD, CORR
[47]	ConvLSTM	Attention	CNTK	USA	2 x 2 km	-	POD, FAR, CSI
[50]	ConvLSTM	LR, FC-LSTM	TensorFlow	China	101 X 101 km	6 minutes	RMSE
[49]	ConvRNN, Multi-layer ConvRNN	ConvLSTM, Eulerian persistence		USA	100 × 100 km		Precision, Recall, F1 score
[48]	TrajGRU	ConvGRU, 2D and 3D CNN, ROVER (nonlinear variant)	-	China	-	-	B-MSE, B-MAE, CSI, HSS
[53]	U-Net CNN	MRMS persistence, HRRR Optical flow method,	Tensorflow	USA	1 × 1km	2 minutes	Precision, Recall
[51]	CNN		Keras, Horovod	USA	256 x 256 km		MSE
[52]	GA-ConvGRU	Optical flow method, ConvGRU	-	China	900 × 900 km		POD, FAR, CSI, HSS
[54]	dec-ConvLSTM, dec-ConvGRU, dec-TrajGRU	TrajGRU, ConvGRU, ConvLSTM	TensorFlow	China	101 × 101 km	6 minutes	CSI, FAR, POD, MSE, MAE, SSIM, MS-SSIM, PCC
[55]	CNN-BiLSTM	ConvLSTM, LSTM, FC-LSTM, AlexNet	-	China	10×10 Km	6 minutes	RMSE
[56]	RainNet (deepCNN)	CNN	Keras	Germany	1 km × 1 km	5 minutes	MAE, CSI, FSS
[57]	ConvLSTM	COTREC,ConvLSTM (with cross entropy loss)	PyTorch	China	1 km x 1 km	6 minutes	CSI
[58]	MAR- CNN	dual-channel CNN attention, dual-channel CNN, single-channel CNN, GBDT, SVM	Tensorflow	China	41 × 41 km	6 minutes	RMSE, EVS

experimental result showed that RainNet significantly outperformed the benchmark models Rainymotion and persistence method at all lead times up to 60 minutes.

ConvLSTM with a star-shaped bridge architecture was implemented by [57] for precipitation nowcasting and compared the performance of the model with Continuous Tracking Radar Echo by Correlation (COTREC) and the ConvLSTM with cross-entropy loss. The authors used Group Normalization to refine the convergence performance in optimization for ConvLSTM and they employed a special multisigmoid loss. Experimental results showed that the proposed model achieved state-of-the-art performance.

[58] proposed Multihead Attention Residual Convolutional Neural Network (MAR-CNN) for short-term precipitation forecasting. The proposed method used two CNN architectures. The first CNN model extracts deep characteristics from radar images and the second CNN model acquired deep features from the non-image input. Multihead attention was also introduced by the authors to emphasize the key areas corresponding to precipitation and a residual connection to avoid global information loss which was caused by the attention layer. The authors compared the MAR-CNN model with dual-channel convolutional attention model, dual-channel convolutional model, single-channel CNN model, Gradient Boosted Decision Tree (GBDT), and SVM. The proposed model was found to have a better prediction performance than the compared models.

C. *Rainfall prediction using Satellite image*

The distribution of rain gauges and radar systems is common but limited to their spatial coverage. In contrast, satellite observation provides coverage over a large area and at regular intervals [59]. There is multiple satellites launch for observation of meteorological phenomena. For decades, researchers have used the data provided by satellites for predicting rainfall and other meteorological phenomena. In this section, we present the literature that implements deep learning methods for rainfall prediction using satellite images. *Table III* summarizes the papers found in the literature.

[60] applied a Stacked Denoising Auto-Encoder (SDAE) for bias correction on satellite precipitation product. The SDAE is used to improve the Precipitation Estimation from Remotely Sensed Imagery using an Artificial Neural Network Cloud Classification System (PERSIANN-CCS). The model was evaluated including the detection of Rain or No-Rain pixels and the detection of amount of rainfall for both warm and cold seasons. The study shows that the proposed model can detect false alarm pixels in the PERSIAN-CCS and it is also able to rectify the bias of the overall precipitation level in the warm and cold seasons.

[61] forecasted short-term precipitation using Cloud-Top Brightness Temperature (CTBT). To forecast the next value of CTBT image, deep learning algorithm LSTM was proposed and the Precipitation Estimation using Remotely Sensed Information using Artificial Neural Networks (PERSIANN) algorithm was used for estimating precipitation from the forecasted CTBT image. The model was compared with RNN with PERSIANN, the Persistency method with PERSIANN,

TABLE III. SUMMARY OF PAPERS WHICH PREDICT RAINFALL USING SATELLITE IMAGE

Author	Methods	Comparison	Country	Spatial Resolution	Temporal Resolution	Lead time	Metrics
[60]	SDAE	PERSIANN-CCS, Stage IV	USA	0.08°	Hourly	-	POD, FAR, HSS, Bias MSE, Variance
[61]	LSTM-PERSIANN	RNN-PERSIANN, Persistency-PERSIANN, Farneback optical flow-PERSIANN, Rapid Refresh	USA	GOES-IR: 0.04°×0.04°, Q2 dataset: 0.01°×0.01°, CTBT data and Q2 dataset: 0.25°×0.25°	GOES-IR: 30 minutes Q2 dataset: 5 minutes	6 hours	CORR, RMSE, POD, FAR, CSI
[63]	PredNet network, ConvGRU	TrajGRU	Japan	0.01°	5 minutes	10 frames (50 minutes)	CSI, HSS
[62]	ConvLSTM	BMA, MSMES	Brazil	0.05°	Daily	1 day	MAE, RMSE
[65]	ConvLSTM	LSTM	-	0.1°	30 minutes	150 minutes	RMSE, Accuracy Bias, ETS, FAR, HSS, ORSS, PFD, TS, RMSE, Success Ratio, CORR, Multiplicative Bias,
[64]	CNN-LSTM	CNN, LSTM, MLP	China	0.05°	Daily	1 Day	RMSE, RB, MAE, CORR

Farneback optical flow with PERSIANN algorithm, and Rapid Refresh (RAPv1.0). The proposed model shows superiority in short-term precipitation forecasting.

[62] proposed rainfall prediction using an ensemble approach based on a deep neural network. A Convolutional LSTM was compared with Bayesian Model Averaging (BMA) and Master Super Model Ensemble System (MSMES) methods for predicting rainfall. The experimental results showed that the proposed model is 50% more precise than the compared models.

[63] proposed precipitation nowcasting model based on PredNet network architecture and compared with TrajGRU method. ConvGRU was used as the unit of PredNet instead of the ConvLSTM unit. The experiment showed that the proposed model achieved state-of-the-art performance in the MovingMNIST++ dataset and an acceptable result in the real precipitation data. The model also consumes less GPU memory compared to the TrajGRU model.

[64] proposed to merge the Tropical Rainfall Measuring Mission (TRMM) 3B42 V7 satellite image, rain gauge output, and thermal infrared images to enhanced the accuracy of quantitative precipitation estimation (QPE). The authors used a combination of CNN and LSTM models to extract the spatial characteristics and time dependence of the merged dataset and compared the accuracy with CNN, LSTM, and MLP models. The CNN-LSTM model considered the time and space dependence of precipitation, thus outperformed the compared models which considered either spatial information only or temporal information only. The authors also showed that under different precipitation intensities the CNN-LSTM model can correct and improved the TRMM data.

A precipitation nowcasting model called Convcast was proposed by [65] to predict short-term precipitation. The authors used Convcast a stack of three ConvLSTM layers for learning the spatial and temporal features and a 3D convolutional layer to predict the precipitation. The eleventh sequence of precipitation was predicted from an input of ten consecutive precipitation sequences at an interval of 30 minutes. The predicted precipitation sequence was further used to forecast precipitation up to 150 minutes. The proposed model was compared with LSTM and four optical flow-based methods- Sparse Single Delta (SparseSD), Sparse, Dense, and Dense Rotation (DenseROT). Based on the authors experiment, LSTM was not suitable for data with Spatio-temporal information and Convcast outperformed the compared models.

IV. RESULTS AND DISCUSSION

A. *Temporal distribution of studies*

In Fig. 1, we plot the temporal distribution of the 45 papers selected for the study. The plotted graph shows an increasing trend in the number of papers published in the area of rainfall prediction using deep learning. In 2019, the number of papers grew significantly, which is 51% of the total papers. This shows that there is an increasing interest in applying deep learning methods for rainfall prediction. The decreased in the number of papers from 2019 to 2020 is because we consider up to the month of June only.

B. *Deep learning methods used for rainfall prediction*

In Fig. 2, the frequency of deep learning methods used by the authors for rainfall prediction is given. From this figure, it can be seen that LSTM (10 papers) and ConvLSTM (9 papers) are the most frequently used methods. AE and SAE are usually used by the authors to discover the predictor variables when the input variables are large. When the input is a satellite image or a radar image, most of the authors used convolutional layers for learning the features of the input. The convolution operators enable to learn the spatial information in addition to

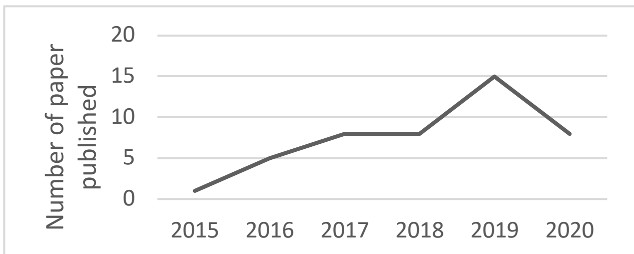

Fig. 1. Frequency of publication during 2015-2020

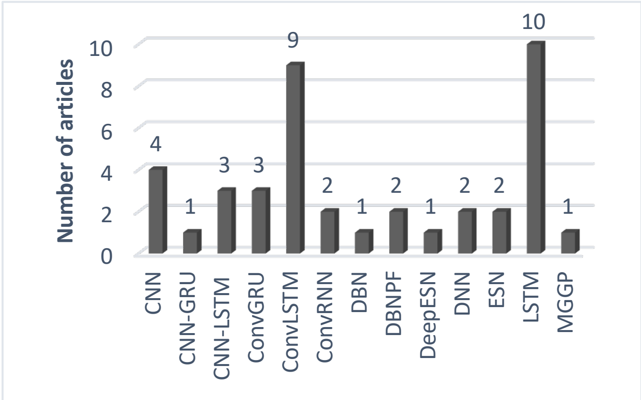

Fig. 2. Frequency of deep learning methods in the surveyed papers

the temporal information. We found that when compared with traditional machine learning models, deep learning models are more accurate for rainfall prediction and they can capture the temporal or spatial information of the input data. When the input data consists of temporal information, traditional machine learning models cannot retain the past information which is required for predicting future rainfall.

C. Spatial distribution of studies

In Fig. 3, we plotted the global distribution of the papers under study. It is based on the country in which the weather data are collected and rainfall is predicted. The Majority of the research was conducted in China (17 papers), followed by India (9 papers) and the USA (6 papers).

D. Software used

The type and frequency of software used for implementing the machine learning models are given in **Error! Reference source not found.**. More than half of the papers (57.8%) mention the software used, whereas 42.2% of the papers did not mention the software used for implementing the machine learning models. We found that MATLAB is the most frequently used software (7 papers), followed by Tensorflow (6 papers) and Keras (5 papers). It seems that due to the easy interface and support for machine learning provided by MATLAB, Tensorflow and Keras are the most used software by the authors. Theano, Python, PyTorch, Platform for Artificial Intelligence (PAI), MapReduce, Hovorod, Microsoft Cognitive Toolkit (CNTK), and Chainer were also used in the paper under study.

E. Performance metrics

In *Table IV* we show the frequency of different performance metrics used in the studied papers. In some papers, the authors did not mention the metrics used, these are not included in the figure. While some authors used a single metric, many authors used multiple metrics for comparing the performance of the models. We found that RMSE was the most commonly used metrics (20 papers), followed by MAE (13 papers), CSI (10 papers), and False Alarm Rate (FAR) (10 papers). Other metrics include Correlation (CORR), Balanced Mean Absolute Error (B-MAE), Balanced Mean Squared Error (B-MSE), Coefficient of Variation (CV), Equitable threat score (ETS), Explained Variance Score (EVS), Fractions Skill Score (FSS), Heidke Skill Score (HSS), Multiplicative Bias (MB), Multi-Scale Structural Similarity (MS-SSIM), Normalized root mean squared error (NRMSE), Odds Ratio Skill Score (ORSS), Pearson

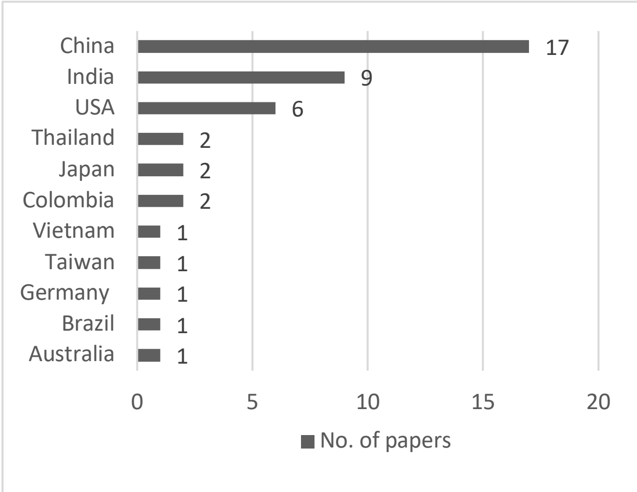

Fig. 3. Global distribution of the papers understudy

Correlation Coefficient (PCC), Probability of False Detection (PFD), Percentage Root mean square Difference (PRD), Stochastic Efficiency of Forecast (SEF), Nash–Sutcliffe Efficiency coefficient (NSE), Relative Bias (RB), Structural Similarity (SSIM), Success ratio and Variance.

V. Future directions

Despite all the research efforts and advancements in the literature, there is still a room for further improvements. In the following, we provide future directions in the area of rainfall predictions.

i) In most of the papers, hyperparameters of the networks are searched using the trial and error method, and few papers used optimization algorithms to find the optimal hyperparameter. Research can be focused in this direction to implement a hybrid model of optimization algorithms and deep learning methods.

ii) Datasets used in most of the papers are weather parameters from a meteorological station or radar image or satellite image. Research can be made to combine the data from the three sources to improve the prediction accuracy.

iii) Due lack of paper that consider all the popular deep learning models with similar dataset and metrics, it is difficult to see which model has the best performance. Thus, efforts can be made in this direction to find the best model.

TABLE I. Frequency of metrics used

No.	Metrics	Papers	No.	Metrics	Papers
1	RMSE	20	18	RB	2
2	MAE	13	19	B-MAE	1
3	CSI	10	20	B-MSE	1
4	FAR	10	21	CV	1
5	POD	9	22	EVS	1
6	CORR	8	23	FSS	1
7	MSE	7	24	MB	1
8	HSS	5	25	MS-SSIM	1
9	TS	5	26	NRMSE	1
10	F1-score	4	27	ORSS	1
11	NSE	4	28	PCC	1
12	Precision	4	29	PFD	1
13	Recall	4	30	PRD	1
14	Accuracy	3	31	SEF	1
15	Bias	3	32	SSIM	1
16	ETS	3	33	Success Ratio	1
17	R-Squared	2	34	Variance	1

VI. CONCLUSIONS

Rainfall prediction is still a challenging task due to the complex and non-linear nature of the weather variables. But due to the high impact of rainfall in our daily lives, it is still a high research area. In this paper, we have surveyed 45 papers published by well-known publishers. We classify rainfall prediction based on the type of data used by the authors. Rainfall and other weather phenomenon are usually collected as the weather parameter value, radar image, and satellite image. We study the deep learning methods applied, types of input data used for the predictor, the type of metrics applied for testing the performance of the models, and the software used for implementing the models. We also study the temporal and spatial distribution of the study. In conclusion, we find that deep learning methods performed better and they are more preferable compared to traditional machine learning models or shallow neural network architecture for the task of rainfall prediction.

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REFERENCES

[1] Y. Dash, S. K. Mishra, and B. K. Panigrahi, "Rainfall prediction for the Kerala state of India using artificial intelligence approaches," *Comput. Electr. Eng.*, vol. 70, no. June, pp. 66–73, 2018, doi: 10.1016/j.compeleceng.2018.06.004.

[2] M. N. French, W. F. Krajewski, and R. R. Cuykendall, "Rainfall forecasting in space and time using a neural network," *J. Hydrol.*, vol. 137, no. 1–4, pp. 1–31, 1992, doi: 10.1016/0022-1694(92)90046-X.

[3] A. Manzato, "Sounding-derived indices for neural network based short-term thunderstorm and rainfall forecasts," *Atmos. Res.*, vol. 83, no. 2-4 SPEC. ISS., pp. 349–365, 2007, doi: 10.1016/j.atmosres.2005.10.021.

[4] H. Meyer, M. Kühnlein, T. Appelhans, and T. Nauss, "Comparison of four machine learning algorithms for their applicability in satellite-based optical rainfall retrievals," *Atmos. Res.*, vol. 169, pp. 424–433, 2016, doi: 10.1016/j.atmosres.2015.09.021.

[5] S. Cramer, M. Kampouridis, A. A. Freitas, and A. K. Alexandridis, "An extensive evaluation of seven machine learning methods for rainfall prediction in weather derivatives," *Expert Syst. Appl.*, vol. 85, pp. 169–181, 2017, doi: 10.1016/j.eswa.2017.05.029.

[6] Y. Lecun, Y. Bengio, and G. Hinton, "Deep learning," *Nature*, vol. 521, no. 7553, pp. 436–444, 2015, doi: 10.1038/nature14539.

[7] C. Shen, "A Transdisciplinary Review of Deep Learning Research and Its Relevance for Water Resources Scientists," *Water Resour. Res.*, vol. 54, no. 11, pp. 8558–8593, 2018, doi: 10.1029/2018WR022643.

[8] S. Khan and T. Yairi, "A review on the application of deep learning in system health management," *Mech. Syst. Signal Process.*, vol. 107, pp. 241–265, 2018, doi: 10.1016/j.ymssp.2017.11.024.

[9] W. Nash, T. Drummond, and N. Birbilis, "A review of deep learning in the study of materials degradation," *npj Mater. Degrad.*, vol. 2, no. 1, pp. 1–12, 2018, doi: 10.1038/s41529-018-0058-x.

[10] S. Pouyanfar *et al.*, "A Survey on Deep Learning," *ACM Comput. Surv.*, vol. 51, no. 5, pp. 1–36, 2019, doi: 10.1145/3234150.

[11] S. Dargan, M. Kumar, M. R. Ayyagari, and G. Kumar, "A Survey of Deep Learning and Its Applications: A New Paradigm to Machine Learning," *Arch. Comput. Methods Eng.*, vol. 27, no. 4, pp. 1071–1092, 2020, doi: 10.1007/s11831-019-09344-w.

[12] H. Ismail Fawaz, G. Forestier, J. Weber, L. Idoumghar, and P. A. Muller, "Deep learning for time series classification: a review," *Data Min. Knowl. Discov.*, vol. 33, no. 4, pp. 917–963, 2019, doi: 10.1007/s10618-019-00619-1.

[13] L. Zhou, C. Zhang, F. Liu, Z. Qiu, and Y. He, "Application of Deep Learning in Food: A Review," *Compr. Rev. Food Sci. Food Saf.*, vol. 18, no. 6, pp. 1793–1811, 2019, doi: 10.1111/1541-4337.12492.

[14] F. Emmert-Streib, Z. Yang, H. Feng, S. Tripathi, and M. Dehmer, "An Introductory Review of Deep Learning for Prediction Models With Big Data," *Front. Artif. Intell.*, vol. 3, no. February, pp. 1–23, 2020, doi: 10.3389/frai.2020.00004.

[15] N. O. Bushara and A. Abraham, "Computational intelligence in weather forecasting: A review," *J. Netw. Innov. Comput.*, vol. 1, no. 1, pp. 320–331, 2013, [Online]. Available: www.mirlabs.net/jnic/index.html.

[16] D. R. Nayak and P. Mahapatra, Amitav\Mishra, "A Survey on Rainfall Prediction using Artificial Neural Network," *Int. J. Comput. Appl.*, vol. 72, no. 16, pp. 32–40, 2013.

[17] D. Chauhan and J. Thakur, "Data Mining Techniques for Weather Prediction: A Review," *Int. J. Recent Innov. Trends Comput. Commun.*, vol. 2, no. 8, pp. 2184–2189, 2014, [Online]. Available: http://ijritcc.org/IJRITCC Vol_2 Issue_8/Data Mining Techniques for Weather Prediction A Review.pdf.

[18] S. Sarumathi, N. Shanthi, and S. Vidhya, "Satellite Rainfall Prediction Techniques - A State of the Art Review," *Int. J. Environ. Chem. Ecol. Geol. Geophys. Eng.*, vol. 9, no. 2, pp. 144–151, 2015.

[19] N. Mishra, H. K. Soni, S. Sharma, and A. K. Upadhyay, "A comprehensive survey of data mining techniques on time series data for rainfall prediction," *J. ICT Res. Appl.*, vol. 11, no. 2, pp. 167–183, 2017, doi: 10.5614/itbj.ict.res.appl.2017.11.2.4.

[20] S. Aftab, M. Ahmad, N. Hameed, M. S. Bashir, I. Ali, and Z. Nawaz, "Rainfall prediction using data mining techniques: A systematic literature review," *Int. J. Adv. Comput. Sci. Appl.*, vol. 9, no. 5, pp. 143–150, 2018, doi: 10.14569/IJACSA.2018.090518.

[21] M. Saha, P. Mitra, and R. S. Nanjundiah, "Autoencoder-based identification of predictors of Indian monsoon," *Meteorol. Atmos. Phys.*, vol. 128, no. 5, pp. 613–628, 2016, doi: 10.1007/s00703-016-0431-7.

[22] M. Saha, P. Mitra, and R. S. Nanjundiah, "Deep learning for predicting the monsoon over the homogeneous regions of India," *J. Earth Syst. Sci.*, vol. 126, no. 4, pp. 1–18, 2017, doi: 10.1007/s12040-017-0838-7.

[23] M. Saha, A. Santara, P. Mitra, A. Chakraborty, and R. S. Nanjundiah, "Prediction of the Indian summer monsoon using a stacked autoencoder and ensemble regression model," *Int. J. Forecast.*, vol. 37, no. 1, pp. 58–71, 2020, doi: 10.1016/j.ijforecast.2020.03.001.

[24] E. Hernández, V. Sanchez-Anguix, V. Julian, J. Palanca, and N. Duque, "Rainfall prediction: A deep learning approach," in *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, 2016, vol. 9648, doi: 10.1007/978-3-319-32034-2_13.

[25] S. Gope, S. Sarkar, P. Mitra, and S. Ghosh, "Early prediction of extreme rainfall events: A deep learning approach," in *Advances in Data Mining. Applications and Theoretical Aspects. ICDM 2016*, 2016, vol. 9728, pp. 154–167, doi: 10.1007/978-3-319-41561-1_12.

[26] P. Zhang, L. Zhang, H. Leung, and J. Wang, "A Deep-Learning Based Precipitation Forecasting Approach Using Multiple Environmental Factors," in *Proceedings - 2017 IEEE 6th International Congress on Big Data, BigData Congress 2017*, 2017, pp. 193–200, doi: 10.1109/BigDataCongress.2017.34.

[27] P. Zhang, Y. Jia, L. Zhang, J. Gao, and H. Leung, "A deep belief network based precipitation forecast approach using multiple environmental factors," *Intell. Data Anal.*, vol. 22, no. 4, pp. 843–866, 2018, doi: 10.3233/IDA-173427.

[28] Q. Ouyang and W. Lu, "Monthly Rainfall Forecasting Using Echo State Networks Coupled with Data Preprocessing Methods," *Water Resour. Manag.*, vol. 32, no. 2, pp. 659–674, 2017, doi: 10.1007/s11269-017-1832-1.

[29] M. Qiu *et al.*, "A short-term rainfall prediction model using multi-task convolutional neural networks," *Proc. - IEEE Int. Conf. Data Mining, ICDM*, vol. 2017-Novem, pp. 395–404, 2017, doi: 10.1109/ICDM.2017.49.

[30] J. Du, Y. Liu, and Z. Liu, "Study of precipitation forecast based on deep belief networks," *Algorithms*, vol. 11, no. 9, pp. 1–11, 2018, doi: 10.3390/a11090132.

[31] K. Yonekura, H. Hattori, and T. Suzuki, "Short-term local weather forecast using dense weather station by deep neural network," in *Proceedings - 2018 IEEE International Conference on Big Data, Big Data 2018*, 2018, pp. 1683–1690, doi: 10.1109/BigData.2018.8622195.

[32] U. Weesakul, P. Kaewprapha, K. Boonyuen, and O. Mark, "Deep learning neural network: A machine learning approach for monthly rainfall forecast, case study in eastern region of thailand," *Eng. Appl.*

Sci. Res., vol. 45, no. 3, pp. 203–211, 2018, doi: 10.14456/easr.2018.24.

[33] D. T. Anh, M. D. Bui, and P. Rutschmann, "A comparative study of three different models to predict monthly rainfall in Ca Mau, Vietnam," in *Hydraulic engineering symposium Graz 2018. Water management - innovation based on tradition*, 2018, no. July, pp. 18–20.

[34] D. Kumar, A. Singh, P. Samui, and R. K. Jha, "Forecasting monthly precipitation using sequential modelling," *Hydrol. Sci. J.*, vol. 64, no. 6, pp. 690–700, 2019, doi: 10.1080/02626667.2019.1595624.

[35] Q. Miao, B. Pan, H. Wang, K. Hsu, and S. Sorooshian, "Improving monsoon precipitation prediction using combined convolutional and long short term memory neural network," *Water (Switzerland)*, vol. 11, no. 5, 2019, doi: 10.3390/w11050977.

[36] S. Viswanath, M. Saha, P. Mitra, and R. S. Nanjundiah, *Deep Learning Based LSTM and SeqToSeq Models to Detect Monsoon Spells of India*, vol. 11537 LNCS. Springer International Publishing, 2019.

[37] M. H. Yen, D. W. Liu, Y. C. Hsin, C. E. Lin, and C. C. Chen, "Application of the deep learning for the prediction of rainfall in Southern Taiwan," *Sci. Rep.*, vol. 9, no. 1, pp. 1–9, 2019, doi: 10.1038/s41598-019-49242-6.

[38] F. Manokij, K. Sarinnapakorn, and P. Vateekul, "Forecasting Thailand's Precipitation with Cascading Model of CNN and GRU," Oct. 2019, doi: 10.1109/ICITEED.2019.8929975.

[39] S. Poornima and M. Pushpalatha, "Prediction of rainfall using intensified LSTM based recurrent Neural Network with Weighted Linear Units," *Atmosphere (Basel).*, vol. 10, no. 11, 2019, doi: 10.3390/atmos10110668.

[40] L. Ni *et al.*, "Streamflow and rainfall forecasting by two long short-term memory-based models," *J. Hydrol.*, vol. 583, p. 124296, 2019, doi: 10.1016/j.jhydrol.2019.124296.

[41] C. J. Zhang, J. Zeng, H. Y. Wang, L. M. Ma, and H. Chu, "Correction model for rainfall forecasts using the LSTM with multiple meteorological factors," *Meteorol. Appl.*, vol. 27, no. 1, pp. 1–15, 2019, doi: 10.1002/met.1852.

[42] K. Zhou, Y. Zheng, B. Li, W. Dong, and X. Zhang, "Forecasting Different Types of Convective Weather: A Deep Learning Approach," *J. Meteorol. Res.*, vol. 33, no. 5, pp. 797–809, 2019, doi: 10.1007/s13351-019-8162-6.

[43] O. Manoj and J. P. Ananth, "MapReduce and Optimized Deep Network for Rainfall Prediction in Agriculture," *Comput. J.*, vol. 63, no. 6, pp. 900–912, 2019, doi: 10.1093/comjnl/bxz164.

[44] J. Pudashine *et al.*, "Deep Learning for an Improved Prediction of Rainfall Retrievals From Commercial Microwave Links," *Water Resour. Res.*, vol. 56, no. 7, pp. 0–3, 2020, doi: 10.1029/2019WR026255.

[45] P. Hewage, M. Trovati, E. Pereira, and A. Behera, "Deep learning-based effective fine-grained weather forecasting model," *Pattern Anal. Appl.*, no. 0123456789, 2020, doi: 10.1007/s10044-020-00898-1.

[46] X. Shi, Z. Chen, H. Wang, D. Y. Yeung, W. K. Wong, and W. C. Woo, "Convolutional LSTM network: A machine learning approach for precipitation nowcasting," *Adv. Neural Inf. Process. Syst.*, vol. 2015-Janua, no. June, pp. 802–810, 2015.

[47] A. Heye, K. Venkatesan, and J. Cain, "Precipitation Nowcasting: Leveraging Deep Recurrent Convolutional Neural Networks," 2017, [Online]. Available: https://cug.org/proceedings/cug2017_proceedings/includes/files/pap155s2-file1.pdf.

[48] X. Shi *et al.*, "Deep learning for precipitation nowcasting: A benchmark and a new model," *arXiv*, no. Nips, pp. 1–11, 2017.

[49] S. Singh, S. Sarkar, and P. Mitra, "Leveraging convolutions in recurrent neural networks for doppler weather radar echo prediction," *Lect. Notes Comput. Sci. (including Subser. Lect. Notes Artif. Intell. Lect. Notes Bioinformatics)*, vol. 10262 LNCS, pp. 310–317, 2017, doi: 10.1007/978-3-319-59081-3_37.

[50] S. Kim, S. Hong, M. Joh, and S. K. Song, "DeepRain: ConvLSTM network for precipitation prediction using multichannel radar data," *arXiv*, pp. 3–6, 2017.

[51] S. Samsi, C. J. Mattioli, and M. S. Veillette, "Distributed deep learning for precipitation nowcasting," *arXiv*, 2019.

[52] L. Tian, X. Li, Y. Ye, P. Xie, and Y. Li, "A Generative Adversarial Gated Recurrent Unit Model for Precipitation Nowcasting," *IEEE Geosci. Remote Sens. Lett.*, vol. 17, no. 4, pp. 601–605, 2019, doi: 10.1109/LGRS.2019.2926776.

[53] S. Agrawal, L. Barrington, C. Bromberg, J. Burge, C. Gazen, and J. Hickey, "Machine learning for precipitation nowcasting from radar images," *arXiv*, no. NeurIPS, pp. 1–6, 2019.

[54] Q. K. Tran and S. K. Song, "Computer vision in precipitation nowcasting: Applying image quality assessment metrics for training deep neural networks," *Atmosphere (Basel).*, vol. 10, no. 5, pp. 1–20, 2019, doi: 10.3390/atmos10050244.

[55] changjiang zhang, H. Wang, J. Zeng, L. Ma, and L. Guan, "Tiny-RainNet: A Deep CNN-BiLSTM Model for Short-Term Rainfall Prediction," *Earth Sp. Sci. Open Arch.*, 2019, doi: 10.1002/essoar.10501344.1.

[56] G. Ayzel, T. Scheffer, and M. Heistermann, "RainNet v1.0: A convolutional neural network for radar-based precipitation nowcasting," *Geosci. Model Dev.*, vol. 13, no. 6, pp. 2631–2644, 2020, doi: 10.5194/gmd-13-2631-2020.

[57] L. Chen, Y. Cao, L. Ma, and J. Zhang, "A Deep Learning-Based Methodology for Precipitation Nowcasting With Radar," *Earth Sp. Sci.*, vol. 7, no. 2, 2020, doi: 10.1029/2019EA000812.

[58] Q. Yan, F. Ji, K. Miao, Q. Wu, Y. Xia, and T. Li, "Convolutional Residual-Attention: A Deep Learning Approach for Precipitation Nowcasting," *Adv. Meteorol.*, vol. 2020, 2020, doi: 10.1155/2020/6484812.

[59] C. Kidd, V. Levizzani, J. Turk, and R. Ferraro, "Satellite precipitation measurements for water resource monitoring," *J. Am. Water Resour. Assoc.*, vol. 45, no. 3, pp. 567–579, 2009, doi: 10.1111/j.1752-1688.2009.00326.x.

[60] Y. Tao, X. Gao, K. Hsu, S. Sorooshian, and A. Ihler, "A deep neural network modeling framework to reduce bias in satellite precipitation products," *J. Hydrometeorol.*, vol. 17, no. 3, pp. 931–945, 2016, doi: 10.1175/JHM-D-15-0075.1.

[61] A. Akbari Asanjan, T. Yang, K. Hsu, S. Sorooshian, J. Lin, and Q. Peng, "Short-Term Precipitation Forecast Based on the PERSIANN System and LSTM Recurrent Neural Networks," *J. Geophys. Res. Atmos.*, vol. 123, no. 22, pp. 12,543-12,563, 2018, doi: 10.1029/2018JD028375.

[62] Y. M. Souto, F. Porto, A. M. Moura, and E. Bezerra, "A Spatiotemporal Ensemble Approach to Rainfall Forecasting," in *Proceedings of the International Joint Conference on Neural Networks*, 2018, vol. 2018-July, pp. 1–8, doi: 10.1109/IJCNN.2018.8489693.

[63] R. Sato, H. Kashima, and T. Yamamoto, *Short-term precipitation prediction with skip-connected PredNet*, vol. 11141 LNCS. Springer International Publishing, 2018.

[64] H. Wu, Q. Yang, J. Liu, and G. Wang, "A spatiotemporal deep fusion model for merging satellite and gauge precipitation in China," *J. Hydrol.*, vol. 584, no. 2006, p. 124664, 2020, doi: 10.1016/j.jhydrol.2020.124664.

[65] A. Kumar, T. Islam, Y. Sekimoto, C. Mattmann, and B. Wilson, "ConvCast: An embedded convolutional LSTM based architecture for precipitation nowcasting using satellite data," *PLoS One*, vol. 15, no. 3, pp. 1–18, 2020, doi: 10.1371/journal.pone.0230114.

[66] M. Saha, P. Mitra, and R. S. Nanjundiah, "Predictor discovery for early-late Indian Summer Monsoon using stacked autoencoder," *Procedia Comput. Sci.*, vol. 80, pp. 565–576, 2016, doi: 10.1016/j.procs.2016.05.337.

[67] F. Manokij, K. Sarinnapakorn, and P. Vateekul, "Forecasting Thailand's Precipitation with Cascading Model of CNN and GRU," in *2019 11th International Conference on Information Technology and Electrical Engineering (ICITEE), Pattaya, Thailand, 2019*, 2019, pp. 1–6, doi: 10.1109/ICITEED.2019.8929975.