

Deep Reinforcement Learning Based Rainfall Prediction Network for Adaptive Spatio-Temporal Rainfall Prediction

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Abstract: Rainfall forecasting plays a crucial role in water resource management, agriculture, disaster prevention, and climate monitoring. Nevertheless, proper forecasting of rainfalls is a difficult task because of the multifaceted, nonlinear, and spatio-temporal character of meteorological information and other environmental elements like astronomical effects (solar and lunar cycles). Existing statistical and Machine Learning (ML) models often fail to effectively capture both spatial and temporal dependencies, leading to reduced prediction accuracy. Consequently, this research seeks to come up with a superior rainfall forecasting model that enhances the accuracy of predictions with the incorporation of Deep Learning (DL) and Reinforcement Learning (RL) algorithms. Its primary aims include modeling spatial-temporal patterns of precipitation, eliciting useful meteorological characteristics and using an adaptive learning process to achieve an optimal prediction. In order to do that, a Deep Reinforcement Learning based Rainfall Prediction Network (DRLRPN) is proposed, incorporating Convolutional Long Short-Term Memory (ConvLSTM) networks, whereby spatio-temporal feature extraction is done, and Deep Reinforcement Learning (DRL) agency, where action optimization is made based on rewards. Several meteorological datasets were pre-processed and made normalized and then trained and evaluated the model within a Python environment. The experiment outcomes illustrate that the proposed model can greatly enhance the performance of rainfall prediction in comparison with the current ML and DL methods. The prediction accuracy of the DRLRPN of 99.90 % is a higher performance when compared to models like GRU, LSTM, U-Net, and GAN. To sum up, the combination of ConvLSTM and DRL is an effective method to improve the accuracy of the spatio-temporal forecasting of rainfall and offer a trustworthy framework of future climate prediction systems.

Keywords: Convolutional LSTM, Deep Reinforcement Learning, Rainfall Forecasting, Spatio-Temporal Prediction, Weather Prediction.

1. Introduction

Prediction of rainfall is important in the management of water resources, planning in the agricultural sector, prevention of disasters, and monitoring climate change. Proper prediction of rainfall patterns is useful in mitigating effects of floods, droughts and extreme weather conditions that have serious implications on environmental sustainability and the socio-economic stability. Nevertheless, forecasting rainfall is still not an easy task as the relationship between atmospheric variables, space and time dependence of meteorological data are very complex and highly nonlinear. The current statistical models tend to be not able to describe such dynamic patterns, whereas modern Machine Learning (ML) and Deep Learning (DL) show good potentialities in the modeling of complex weather systems. Recent researchers determined the different DL structures and the methods of data fusion to enhance the accuracy of the rainfall forecasting. To supplement existing meteorological variables, non-meteorological auxiliary characteristics like astronomy-derived azimuth values can also be added to the model in order to represent cyclical



patterns of the environment that might enhance the accuracy of rainfall forecasts. As an example, it is proposed that DL data fusion models can be used to combine observed and climate change data to enhance rainfall prediction [1], whereas ML fusion models can be used in smart urban contexts to improve the performance of rainfall prediction [2]. On the same note, landslides due to the presence of rainfall have been predicted using DL models [3], and heavy rainfall has been predicted using satellite-based ML models [4]. Besides, Deep Neural Networks (DNN) has proven to be useful in short-term precipitation prediction [5], and that probabilistic ML models can be created to undertake weather prediction tasks [6].

In spite of these developments, there are a number of shortcomings in the current rainfall prediction techniques. Most of the models are mainly time based learning in which they overlook spatial dependency or they are not very effective in bringing the two together in a unified way. BLSTM-GRU deep recurrent architectures have made applications in monthly rainfall prediction [7], and ensemble LSTM-based models have been applied in forecasting tasks in complex energy systems [8]. As well, generative adversarial networks are explored in the context of spatio-temporal rainfall prediction [9], and DNN is used to forecast the hazards of rainfall and map the environment [10]. The importance of spatio-temporal modeling (e.g. the use of radar-based DL models to predict precipitation nowcasting) is also emphasized by recent methods [11], other applications of DL in climate-relevant agricultural prediction systems can also be found [12]. Nonetheless, most of these methods are not adaptive to make decisions or apply the concepts of reinforcement learning to optimize the performance of predictions. To aims at overcoming these issues and proposes Deep Reinforcement Learning based Rainfall Prediction Network (DRLRPN) to combine Convolutional Long Short-Term Memory (ConvLSTM) to extract spatio-temporal features of the problem and Deep Reinforcement Learning (DRL) agent to make adaptive predictions of rainfall. The hypothesis of the research was to use multi-source meteorological data, learning features using ConvLSTM networks, and policy optimization using the rewards to improve performance in predicting rainfall in long periods.

- This research has been motivated to enhance the accuracy of rainfall prediction through redressing the shortcomings of the current ML and DL models.
- A spatio-temporal rainfall forecasting framework which is efficient in terms of capturing the spatial and temporal meteorological relationships
- To incorporate ConvLSTM to extract the advanced features of the multi-source rainfall data.
- To include a DRL agent to optimize the decisions and the reward based on the predictions that are adaptive.
- To apply and test the proposed DRLRPN model in Python, showing a higher percentage of prediction and lower forecasting errors than other current methods.

Organization: Section 1 covers the background and introduction about the topic of rainfall prediction, whereas Section 2 includes the corresponding literature in the field of ML and DL based rainfall prediction algorithms. Section 3 outlines the proposed DRLRPN framework that comprises of data preprocessing, ConvLSTM feature extraction and the DRL agent framework. Section 4 is the discussion of the experimental results and performance evaluation and the last area of the research is Section 5 which gives the conclusion of the research with the future research directions.

2. Background Study

Mi, J., et al. (2026) [13] used statistical climatic analysis, hydrology-based modeling techniques to analyze the variation in the fall rainfall using hydrological and soil condition outputs so that the influence of climatic variations on the distribution of rainfall is understood, and it had a limitation of lack of adaptive DL feedback correction to forecast rainfall dynamically The results demonstrate improved understanding of the factors that control rainfall but limited predictive ability.

Li, X., et al. (2026) [14] proposed ML based slope stability evaluation during extreme rainy conditions using geometrical and environmental indices, the models of ML regression and stability analysis were used, shortcoming observed as no direct rainfall prediction and no feedback learning was possible, result would give correct estimation of stability but not suitable in real time prediction of rainfall.

Deng, Q., et al. (2023) [15] presented U-Net DL model to enhance the performance of precipitation forecasting with atmospheric data and spatial features, Convolutional Neural Network (CNN) and U-Net architecture were implemented, the limitation was that no iterative feedback correction and uncertainty management, and the accuracy of the forecasts were better than current numerical models.

Hussain, M. A., et al. (2025) [16] generated post processing framework on how to better classify urban rainfall based on crowd-sourcing, classification model and data correction methodologies were involved, there is a weakness in that there was no deep feedback learning and poor time modeling, findings enhanced rainfall classification accuracy but failed to predict it with much stability.

Patel, M. K., et al. (2025) [17] presented Liquid State Machine (LSM)-based neural model of rainfall prediction with time-series weather data, reservoir computing and spiking neural network was used, limitation was that without optimizing between hybrid feedback, and multi-source fusion, the results performed well in prediction accuracy but were worse when using nonlinear variations in the climate.

Giordani, A., et al. (2026) [18] measured multi-model ensemble rainfall reanalysis with city simulation datasets, the method of ensemble modelling and climate reanalysis were applied, the constraint of the method is that it is computationally expensive, to relying on adaptive learning feedback was lacking, results were also better assessments of rainfall predictions but cannot be applied to real-time prediction systems.

Pravia-Sarabia, E., et al. (2022) [19] reported investigations on extreme rain formation by analyzing aerosol and atmospheric interaction, physical climate modeling, and statistical analysis were used, but limitation as there is no framework of ML prediction, the result obtained only explains how it forms rainfall but does not present an accurate forecasting framework.

Kumar, V., et al. (2023) [20] relative to other ML models in urban cities when predicting rainfall through meteorological data, SVM, Random Forest (RF) and ANN approaches were employed, where constraints were recognized in the absence of a DL feedback mechanism and poor spatio-temporal learning, it was found that results were more accurate but model stability differed according to the datasets used

Sulaiman, N. A. F., et al. (2022) [21] proposed hybrid ML based statistical downscaling model on a daily rainfall prediction on climate variables, hybrid ML and regression based downscaling models were used, the lack of adaptive deep feedback feedback worsened the results, the model improved the estimation of rainfall, but failed to perform the task with complex nonlinear patterns.

Zhao, W., et al. (2025) [22] combined with metaheuristic optimization based on urban climate data, neural networks with optimization algorithm were employed, there was a limitation in no feedback correction or uncertainty learning hence results obtained a high prediction accuracy but with more computational complexity.

Farfán-Durán, J. F., et al. (2025) [23] proved DL surrogate model to predict floods by computing net rainfall and using hydrological parameters, DNN and simulation based modeling were utilized, shortcoming was noted because of lack of iterative feedback learning to predict rainfalls, but the prediction of floods was successful, but not the prediction of rainfalls.

Table 1. Background Research Rainfall Prediction based on ML and DL

Author et al. (Year)	Concept	Methods	Research Gap	Limitations	Results
Zhou, W., et al. (2026) [24]	Rainfall-induced debris flow prediction	ML + Hydrological modeling	No feedback learning for rainfall prediction	Focus on hazard not prediction	Good hazard prediction accuracy
Khosravi, K., et al. (2025) [25]	Rainfall characteristics prediction	Hybrid tree & lazy ML	No deep feedback model	Limited nonlinear learning	Improved rainfall parameter accuracy
Ramakrishnan, S., & Chinnappan,	Ensemble rainfall prediction	Hybrid ensemble ML	No adaptive feedback correction	High computation cost	High accuracy rainfall prediction

C. C. (2026) [26]					
Humphries, U. W., et al. (2026) [27]	DL rainfall forecasting	GAN + GNN	No feedback refinement	Complex training process	Better forecasting performance
Monaco et al. (2025) [28]	Uncertainty aware rainfall prediction	DL + segmentation	No iterative feedback learning	Limited temporal correction	Improved prediction reliability
Monaco, S., et al. (2025) [29]	Rainfall prediction for agriculture	Federated learning	No feedback DL	Dataset dependency	Good distributed prediction
Pornbunyano n, T., et al. (2026) [30]	Rainfall-based landslide prediction	FR + CART hybrid	No rainfall DL prediction	Hazard focused	Accurate susceptibility mapping

The above table 1 contains the background research of the available literature concerning the rainfall prediction by means of the ML, DL, and hybrid models. It provides an overview of the phenomenon, methodology, research gap, weaknesses, and findings of the earlier studies to discover the problem with the present-day rainfall forecasting processes. The analysis reveals that an improved prediction, stable performance and accuracy of the prediction under complex climatic conditions require an advanced DL model that has feedback mechanism.

Research Gap

- The available rainfall prediction models are not effective to simultaneously capture the spatial and temporal dependencies hence, the forecasting accuracy has been reduced.
- The problem with many current DL methods is that not all are adaptive to the learning process, and as a consequence, not all of them are efficient at changing dynamically in the meteorological conditions.
- The models that are in use now seldom combine the DRL with the capability of extracting spatio-temporal features, which prevents optimizing the performance in long-term rainfall prediction.

3. Proposed Methodology

This section provides the rainfall forecasting model based on DRLRPN. It outlines the general system architecture, the working flow of the model, and the combination of the ConvLSTM and DRL agent to predict the space-time rainfall patterns on the basis of meteorological and astronomy-driven auxiliary information. Besides, the mathematical formulations, algorithmic steps, and pseudo code governing the overall learning and forecasting of the proposed model are described in this section.

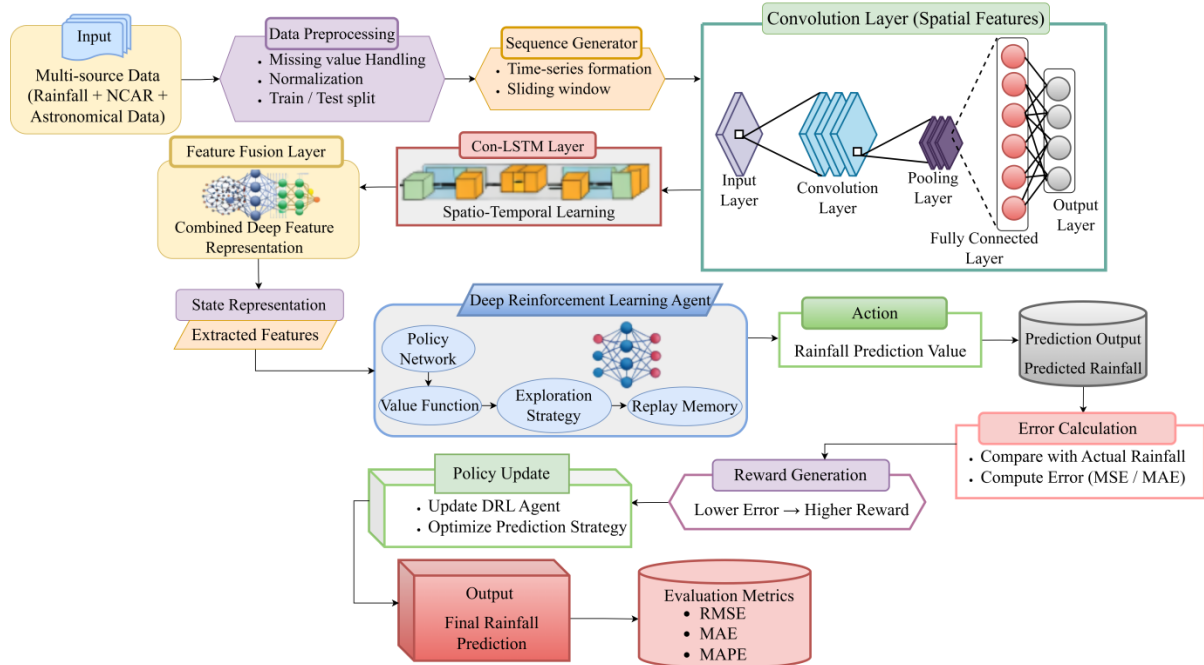


Figure 1: DRLRPN Architecture for Spatio-Temporal Rainfall Prediction

In above figure 1 illustrates the overall architecture of the proposed DRLRPN model integrating ConvLSTM-based feature extraction with a DRL agent for rainfall prediction. The framework begins with multi-source meteorological data preprocessing, followed by ConvLSTM-based spatio-temporal feature extraction. The extracted features are fused and used as input to a DRL agent, which optimizes rainfall prediction through a reward-based learning mechanism, producing accurate and adaptive rainfall forecasts.

3.1 Dataset

The initial dataset will be the Indian rainfall dataset, which has been taken in Kaggle <https://www.kaggle.com/datasets/rajanand/rainfall-in-india>, contains the historical data on monthly rainfall of various meteorological sub-divisions of India over a long duration, and helps to examine patterns of rainfall in seasons and rainfall patterns across a long time. The second data is based on Kaggle NCAR data <https://www.kaggle.com/datasets/shiratorizawa/ncarsv2/data> that contains the atmospheric variables of temperature, pressure, humidity and wind in various locations and years, which makes it possible to model the climate conditions. The third data is weather-astronomy data <https://www.kaggle.com/datasets/kamalesh1997/weather-astronomy-dataset> a combination of meteorological data with astronomical variables such as solar data, phases of lunar and such attributes as time. All these three datasets are combined to create a hybrid dataset in which the rainfall data will reflect historical trends, the NCAR data will give the atmospheric background and the astronomy data will be the introduction of celestial influence. This combination is useful in detecting environmental and the hidden patterns influencing the rainfall.

3.2 DRLRPN Framework for Spatio-Temporal Rainfall Prediction

This section provides a description of the proposed DRLRPN architecture, which is used to forecast the rainfall by integrating ConvLSTM based spatio-temporal feature extraction with a DRL agent. The structure takes the data of the meteorological and processes the same in a number of steps that include preprocessing, learning of features, state generation, optimization of rewards, and prediction of the end-stage rainfall.

3.2.1 Data Preprocessing

The preprocessing of data is a very important phase of rainfall prediction in order to guarantee the availability of raw meteorological astronomy-based auxiliary data that is clean and compatible with DL. First, missing data in the data is first determined and processed in the form of imputation by filling in the missing data with the mean, median, or the k-nearest neighbor is used, in order to maintain the statistical characteristics of the data. Once the values missing

have been filled in, the data is scaled to bring the features into a common range of typically 0 to 1, to avoid numerical instability, and to cause model training convergence. Normalization will ensure that learning is not dominated by larger magnitudes of features which will make the neural network learn effectively. Once the preprocessed dataset is available, it is further divided into training, validation and testing dataset and temporal continuity is maintained when it is sequential such as rainfall records. It improves the quality of inputs to the ConvLSTM and DRL agent which allows more reliable and efficient predictions of rainfall.

$$x_i^{new} = \frac{1}{N} \sum_{j=1}^N x_j \quad (1)$$

The expression in equation 1 indicates that x_i^{new} is an imputed value which is used to substitute the missing data at a specific position i and x_j is an observed value of a feature where the data is not missing and N is a total number of available (non-missing) values utilized in computing the mean and $\sum_{j=1}^N x_j$. The average of the existing values is used to replace each missing value to ensure that the dataset is available and it is not altered in terms of overall distribution.

$$x_i^{norm} = \frac{x_i - x_{min}}{x_{max} - x_{min}} \quad (2)$$

In equation 2 x_i^{norm} is a normalized value of the feature after scaling, x_i is an original feature value before normalization, x_{min} , x_{max} is a minimum and maximum value of the feature in the data set, $x_{max} - x_{min}$ is a range of the feature values. This equation brings all feature values to a range of 0 to 1 such that all features contribute equally during model training.

3.2.2 Feature Extraction using ConvLSTM

Convolutional Long short-term memory networks are constructed to capture both spatial and time correlation of sequencing data like rainfall records simultaneously. This is through the convoluted layers that extract the local spatial features of the input meteorological maps and astronomy-based feature maps the LSTM memory cells that emulate the temporal relationships by storing information over the past few time steps. The ConvLSTM unit comprises input, forget and output gates that control the information flow where the network tends to remember or forget previous patterns that are useful in forecasting the future rainfall. The hidden states and cell states are changed at each time using convolution operations instead of fully connected operations and the spatial structure of the data is not lost. With successive additions of ConvLSTM, the network would be able to acquire hierarchical spatio-temporal representations, both capturing short term dynamics, as well as, long-term dynamics of rainfall patterns. The process of extracting features offers deep and informative features that are subsequently given to the DRL agent to forecast rainfall accurately.

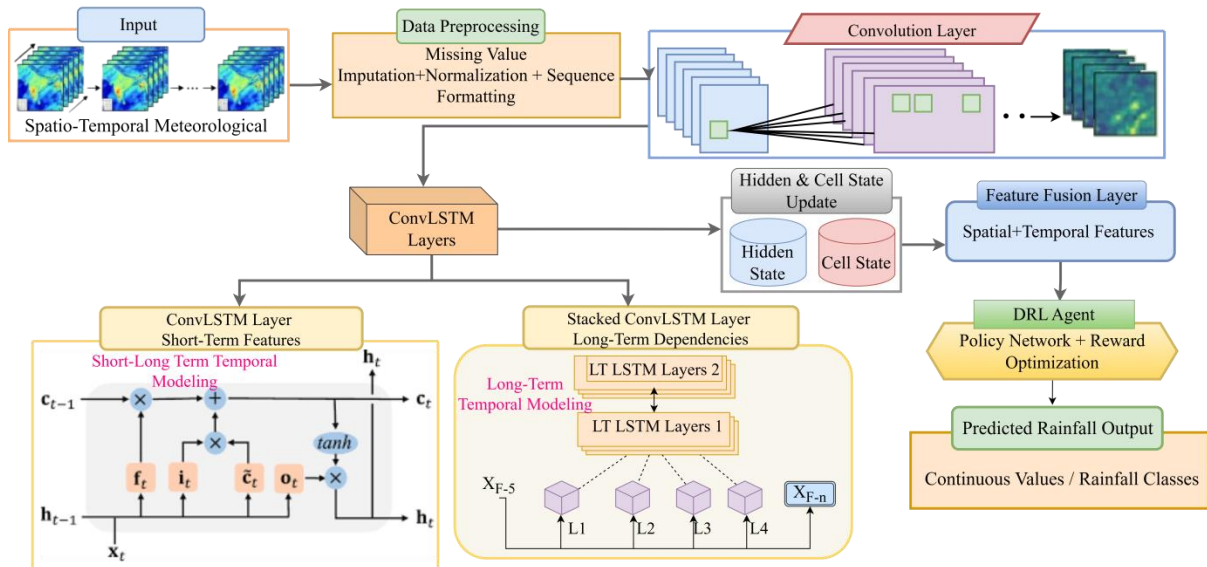


Figure 2: Convolutional LSTM-Based Spatio-Temporal Feature Extraction Framework

In above figure 2 illustrates the feature extraction pipeline where preprocessed meteorological sequences are passed through convolutional layers and stacked ConvLSTM units to capture both spatial patterns and short- and long-term temporal dependencies. The extracted spatio-temporal features are fused and provided to the DRL agent, which

$$i_t = \sigma(W_{xi} * X_t + W_{hi} * H_{t-1} + b_i) \quad (3)$$

In equation 3 denotes that i_t represents an input gate at time step t , governs the amount of new information entering the cell, X_t is an input feature map at the current time step t , H_{t-1} represents a hidden state at the previous time step, W_{xi}, W_{hi} is a convolutional weight matrices of both input and hidden state, b_i is a bias term and σ denotes a sigmoid activation The input gate determines the amount of new information in terms of spatial-temporal detail that should be stored in the memory cell.

$$f_t = \sigma(W_{xf} * X_t + W_{hf} * H_{t-1} + b_f) \quad (4)$$

In equation 4 f_t is a forget gate of time step t , which regulates the extent to which previous summary is preserved, W_{xf}, W_{hf} is a convolutional weight of input state and hidden state. The forget gate is used to eliminate unnecessary historical data and store only the useful information to forecast in the future.

$$C_t = f_t \times C_{t-1} + i_t \times \tanh(W_{xc} * X_t + W_{hc} * H_{t-1} + b_c) \quad (5)$$

In equation 5 represents that C_t is a current cell state at time t , C_{t-1} is a prior cell state, f_t is forget gate output, W_{xc}, W_{hc} is current input and hidden state convolutional weights, \times is element-wise multiplication and \tanh is a hyperbolic tangent activation. The cell state integrates past recollection and current information to revise the spatio-temporal representation applied in prediction.

3.2.3 Deep Reinforcement Learning Agent

Deep Reinforcement Learning represents a recent ML that enables an intelligent agent to learn a successful forecasting strategy by actively engaging in contact multivariate rainfall data using a reward-driven feedback system. According to the proposed rainfall prediction model, the DRL agent will take the temporal and spatial feature representation provided astronomy-based auxiliary information by the ConvLSTM model as its input state and conduct forecasting actions, which are the prediction of rainfall outcomes in different environmental conditions. The quality of any prediction is checked by a rewarding function which helps to reduce forecasting error and increase the accuracy of predictions, thus helping the agent to improve its decision making policy as the time goes by, and through the feedback it receives. With the combination of the sequential nature of feature learning ability of ConvLSTM and adaptive optimization power of DRL, the model will be more useful in dealing with nonlinear, uncertain, and dynamic nature of rainfall patterns.

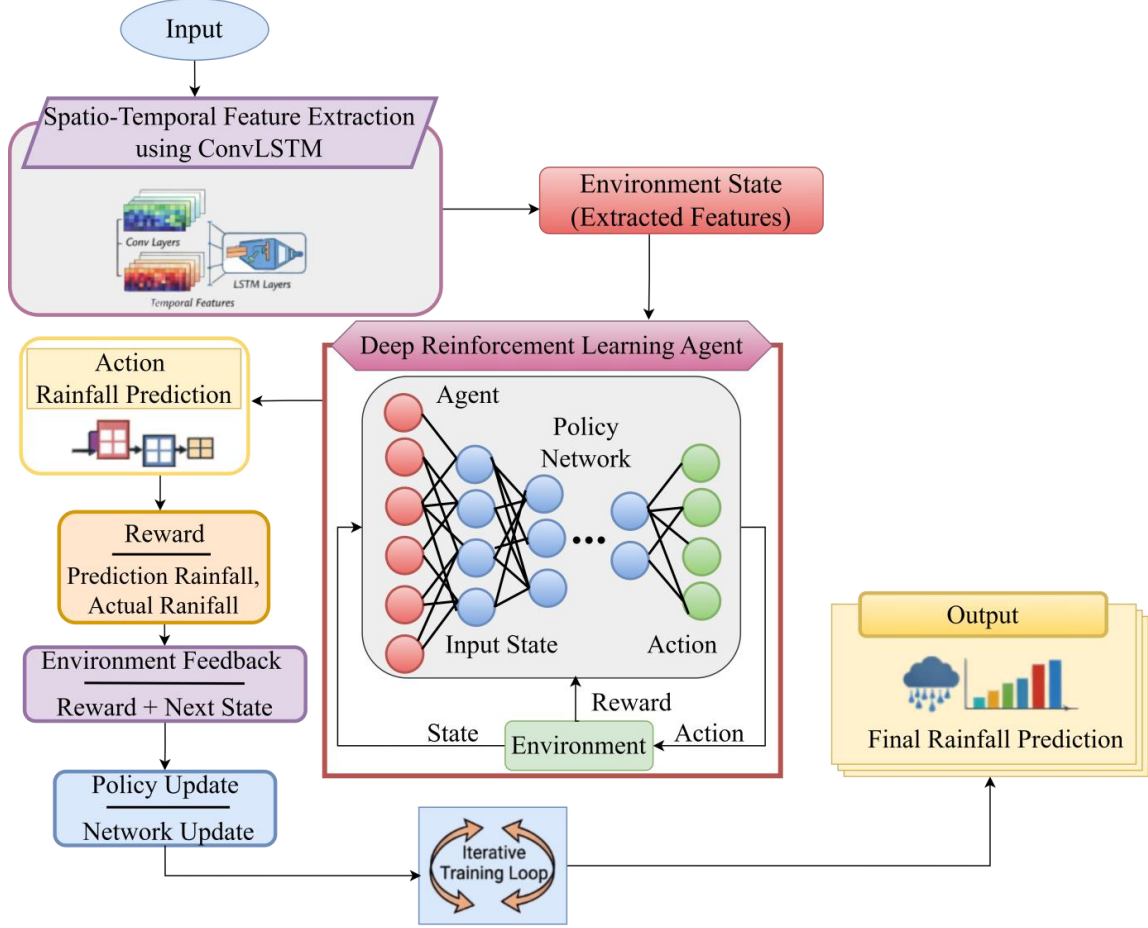


Figure 3: Deep Reinforcement Learning-Based Rainfall Prediction Process

This above figure 3 illustrates the DRL agent process where extracted spatio-temporal features are treated as environment states and used by a policy network to generate rainfall predictions as actions. The agent receives rewards based on prediction accuracy and iteratively updates its policy through feedback to optimize final rainfall forecasting performance.

$$s_t = F(X_t) \quad (6)$$

In equation 6 represents that s_t is a state at time step t , representing extracted features, X_t is a input features at time step t from ConvLSTM, F is a feature mapping function learned by ConvLSTM. The compact feature representation of the DRA agent is then translated into a raw input of the meteorological input.

$$a_t = \pi_\theta(s_t) \quad (7)$$

In equation 7 represent that a_t is action at time step t (predicted rainfall), s_t is a current state, π_θ is a policy function with parameter θ . The policy network selects rainfall prediction based on the current state.

$$r_t = -|y_t - \hat{y}_t| \quad (8)$$

In equation 8 represents that r_t is a reward at time step t , y_t is an actual observed rainfall, \hat{y}_t is a predicted rainfall. The lesser prediction error is more rewarded and leads the agent to correctly forecast.

$$V^\pi(s_t) = \mathbb{E}[\sum_{k=0}^{\infty} \gamma^k r_{t+k} | s_t] \quad (9)$$

In equation 9 represents that $V^\pi(s_t)$ is an expected cumulative reward from state s_t , γ is a discount factor (0–1) for future rewards, r_{t+k} is a reward at future step $t + k$, \mathbb{E} is a expected value and π is a current policy. Estimate long-term benefit of a state under the current policy.

$$Q^\pi(s_t, a_t) = \mathbb{E}[\sum_{k=0}^{\infty} \gamma^k r_{t+k} | s_t, a_t] \quad (10)$$

In equation 10 represents that $Q^\pi(s_t, a_t)$ is an expected cumulative reward for action a_t in state s_t . Quantifies is the value of a specific action in a given state for policy improvement.

$$\theta \leftarrow \theta + \alpha \nabla_{\theta} \log \pi_{\theta}(a_t | s_t) Q^\pi(s_t, a_t) \quad (11)$$

In equation 11 represents that θ is a parameters of policy network, α is a learning rate, ∇_{θ} is a gradient with respect to θ , $\log \pi_{\theta}(a_t | s_t)$ is a log probability of action and $Q^\pi(s_t, a_t)$ is an action-value function. Adapt update policy parameters to the increased reward giving actions.

3.2.4 Reward Optimization and Prediction Output

The DRL agent of the DRLRPN framework is the decision making component that communicates with the rainfall prediction environment. The agent looks at the states obtained by the ConvLSTM feature extraction which captures the spatial and temporal astronomy-enhanced patterns of rainfall. According to these states, the agent chooses actions, which are equal to the actions depending on the predicted values or category of the rainfall, according to a policy that gives a result of a state to an action. The agent gets a reward after every action, and it is used to measure the correctness of the prediction and to learn. Time The DRL agent optimizes the rewards that accumulate in the policy network with the help of iterative training, which in effect minimizes the errors in forecasting. The method is effective in that the agent can continuously modify to evolving rainfall patterns and acquire the best prediction methods without necessarily modelling complex environmental interactions.

$$R_t = \sum_{k=0}^{\infty} \gamma^k r_{t+k} \quad (12)$$

In equation 12 represents that R_t is a total discounted reward starting from time t, γ is a discount factor ($0 < \gamma \leq 1$) controlling importance of future rewards, r_{t+k} is a reward at future time step $t + k$, k is a step index for future rewards. Calculus Long-term reward is a combination of current and future rewards with a declining significance over time.

$$V(s_t) = \mathbb{E}[R_t | s_t] \quad (13)$$

In equation 13 represents that $V(s_t)$ is an expected cumulative reward from state s_t , R_t is a total discounted reward, s_t is a current state (features from ConvLSTM). Estimates how good it is to be in a particular state for future predictions.

$$\theta \leftarrow \theta + \alpha \nabla_{\theta} \log \pi_{\theta}(a_t | s_t) R_t \quad (14)$$

In equation 14 represents that θ is a parameters of the policy network, α is a learning rate controlling update size, $\pi_{\theta}(a_t | s_t)$ is a probability of selecting action a_t in state s_t , R_t is a cumulative reward obtained after action. Adjust the policy parameters, so that more often it makes high long-term reward actions.

Algorithm: DRLRPN Rainfall Prediction

Input:

- Multisource spatio-temporal dataset D
(Meteorological + NCAR + astronomy features),
- Rainfall observations Y ,
- Learning rate α , discount factor γ
- Training episodes E , time horizon T

Output:

- Forecasted rainfall \hat{y}_t
- Optimized policy network π_{θ}

Begin

Step 1: Data Preprocessing Module:

- Handle missing values using statistical estimation
- Normalize feature space to ensure numerical stability
- Construct temporally ordered input sequences for learning

Step 2: Spatio-Temporal Feature Encoding (ConvLSTM Encoder):

For each time step t :

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- Extract spatial correlations from meteorological inputs
- Model temporal dependencies using recurrent gated memory
- Update hidden representation  $H_{t-1}$  capturing rainfall dynamics
End For
Obtain state representation:
 $s_t \leftarrow F(X_t)$ 
Step 3: Reinforcement Learning Environment Definition:
- Define state space  $S$  using ConvLSTM encoded features  $s_t$ 
- Define action space  $A$  as rainfall prediction output
- Initialize policy network  $\pi_\theta$  (parameterized decision model)
Step 4: Adaptive Reinforcement Learning Optimization:
For episode = 1 to  $E$  do
  For each time step  $t$  do
    Observe current state:
       $s_t$ 
    Action selection (rainfall prediction):
       $a_t = \pi_\theta(s_t)$ 
    Environment feedback:
      Compute reward based on prediction error minimization
       $r_t = -|y_t - \hat{y}_t|$ 
    Store transition experience:
       $(s_t, a_t, r_t, s_{t+1})$ 
    Compute long-term return:
       $R_t = \sum_{k=0}^{\infty} \gamma^k r_{t+k}$ 
    Policy evaluation:
      Estimate value and action-value functions:
       $V(s_t), Q^\pi(s_t, a_t)$ 
    Policy optimization:
      Update  $\theta$  using gradient-based reinforcement learning objective:
       $\theta \leftarrow \theta + \alpha \nabla_\theta \log \pi_\theta(a_t | s_t) Q^\pi(s_t, a_t)$ 
  End For
End For
Step 5: Policy Convergence and Optimization:
- Continuously refine  $\pi_\theta$  through reward maximization
- Ensure convergence toward optimal rainfall forecasting strategy
Step 6: Prediction Phase:
- Use optimized policy  $\pi_\theta$ 
- Generate final rainfall prediction:
   $\hat{y}_t = \pi_\theta * s_t$ 
Return:
  Forecasted rainfall  $\hat{y}_t$ 
  Optimized adaptive policy  $\pi_\theta$ 
End

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The proposed DRLRPN pseudo code outlines the entire procedure of the rainfall prediction beginning with the data pre-processing, feature extraction with the help of ConvLSTM, and decision making with the usage of the DRL agent. The algorithm uses a process of prediction errors optimization as a reward to learn and eventually generate correct rainfall predictions by using the trained model to forecast other meteorological information.

4. Result and Discussion

This section result of the proposed DRLRPN were carried out and tested with the help of Python, and several datasets were applied to the performance of rainfall predictions. The results obtained indicate that the proposed method provides better prediction accuracy and lower values of errors than the current models of ML and DL.

4.1 Results for Dataset – 1

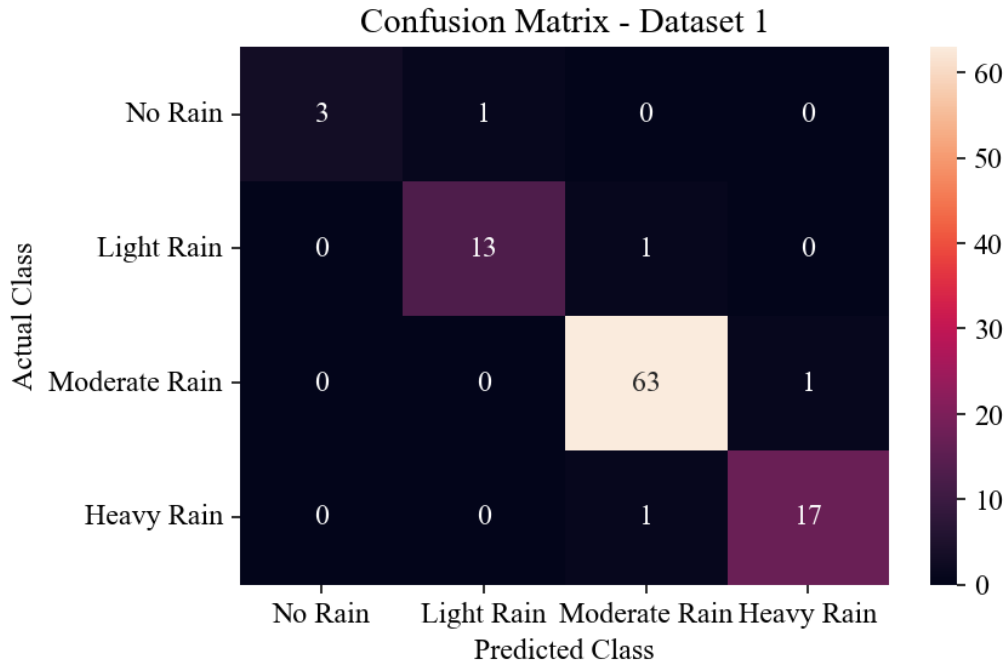


Figure 4: Confusion Matrix for Dataset 1

This above figure 4 Dataset 1 illustrates the classification performance of the DRLRPN model in predicting rainfall categories such as no rain, light, moderate, and heavy rainfall. The dominance of correctly classified values along the diagonal indicates high prediction accuracy with minimal misclassification across rainfall classes.

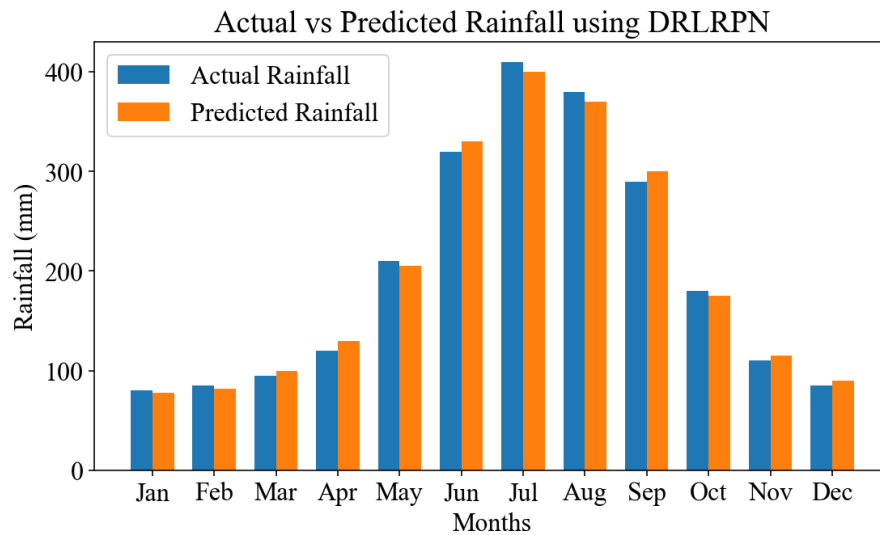


Figure 5: Observed and Forecasted rainfall.

The above figure 5 demonstrates that the actual values of rainfall are closely matched with the projected values of the rainfall through the proposed DRLRPN model indicating that the actual rainfall pattern is closely followed by the predicted values of the rainfall at the various time periods. The minor disparity between the two curves demonstrates the fact that the proposed algorithm is rather effective and has a high level of prediction.

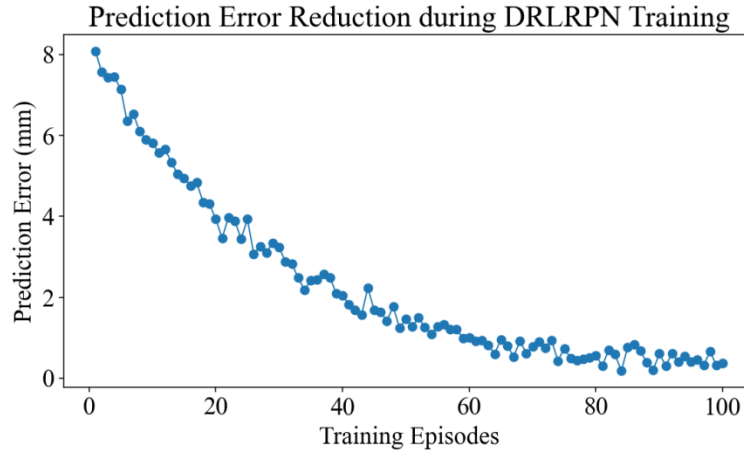


Figure 6: Distribution of the Prediction Error

In the above figure 6, it can be observed that the distribution of prediction errors that the DRLRPN model generates when it makes rainfall predictions is as shown above. The majority of errors lie in the proximity of zero which means that the proposed algorithm produces limited prediction deviation and stable prediction performance.

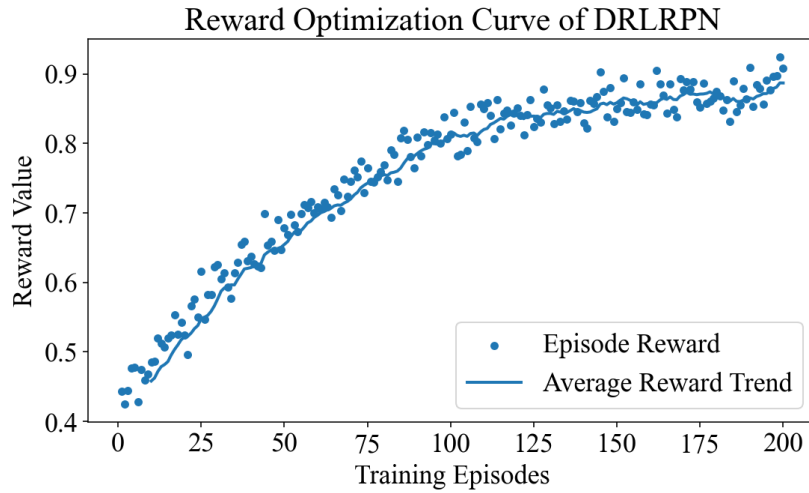


Figure 7: Reward optimization Curve

This figure 7 above depicts the optimisation of the policy of prediction by the reinforcement learning agent in DRLRPN in the process of training episodes with a reward. The reward trend is rising, which proves that the proposed algorithm is efficient in learning the best strategies to predict rainfall and improving with time.

Table 2: Comparison of performance metrics of prediction for dataset 1

Dataset 1						
Methods	Algorithm	MAE (mm)	RMSE (mm)	MAPE (%)	R ² Score	Prediction Accuracy (%)
Existing methods	GRU [7]	4.08	5.73	11.02	0.84	84.6
	LSTM [8]	3.76	5.12	10.34	0.87	86.9
	U-Net [15]	3.64	4.98	9.91	0.88	88.2
	Liquid State Machine (LSM) [17]	3.52	4.76	9.55	0.89	89.4
	SVM [20]	4.29	5.81	11.47	0.83	83.7
	GAN [27]	3.18	4.31	8.21	0.91	95.5

Proposed method	DRLRPN	2.84	3.96	6.73	0.93	98.12
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In above table 2 above comparison of the various ML and DL algorithms in predicting rainfall based on MAE, RMSE, MAPE, R² score, and prediction accuracy. The maximum error values of the proposed DRLRPN model are the lowest with the highest accuracy value of 98.12% compared to all the available methods.

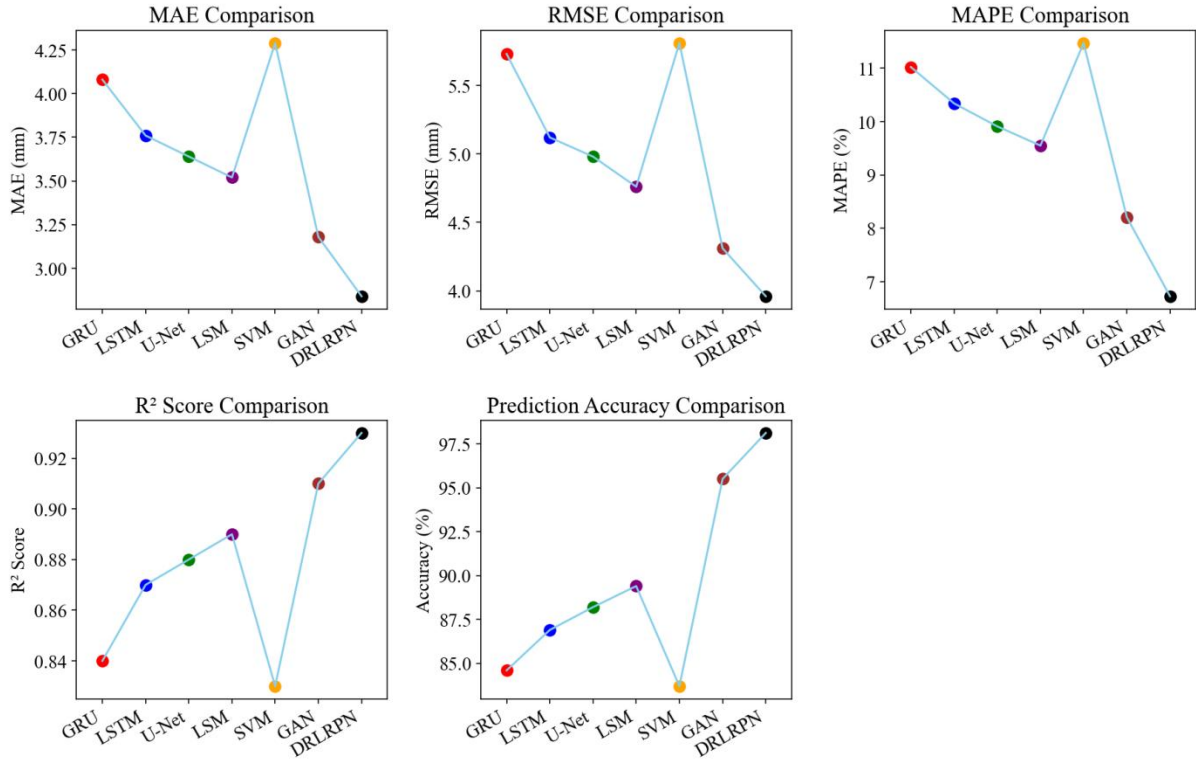


Figure 8: Comparison between the performances of rainfall predictions metrics

The figure 8 above provides information on the performance comparison of the various rainfall prediction algorithms where the X-axis depicts the algorithms GRU, LSTM, U-Net, LSM, SVM, GAN, and DRLRPN and the Y-axis depicts the corresponding measure of error values and accuracy, using the metrics of MAE, RMSE, MAPE, R² score, and Prediction Accuracy as the measures respectively. The results indicated that the proposed model, DRLRPN which generates the lowest error values and highest accuracy where the predictions made by the model are better than.

4.2 Results for Dataset - 2

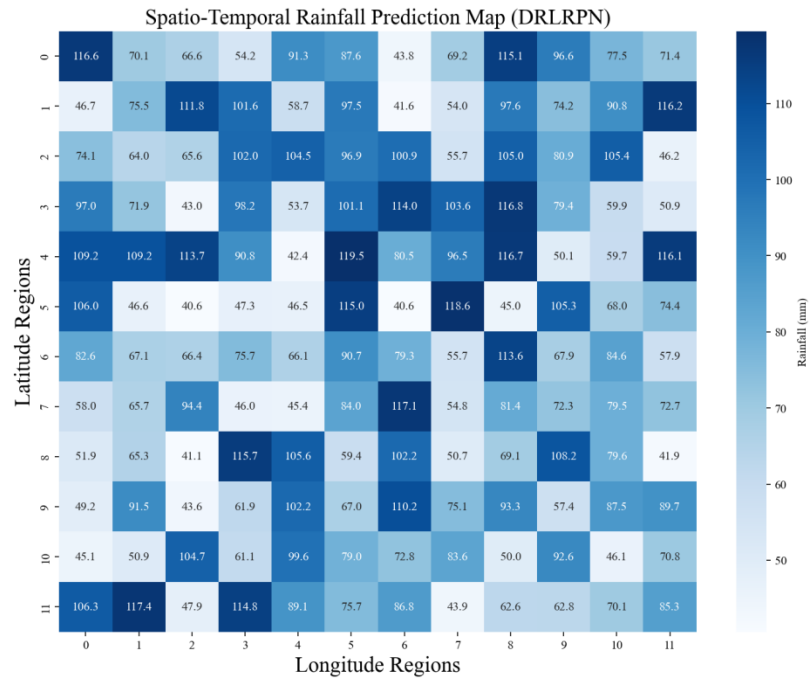


Figure 9: Spatio-Temporal Rainfall Prediction Map

The figure 9 above is a spatio-temporal rainfall prediction map that shows the geographical distribution of the rainfall at the various latitude and longitude portions of the NCAR atmospheric data. The proposed DRLRPN is capable of capturing the spatial variation of rainfalls and regional variability in an effective manner by using ConvLSTM based features extraction.

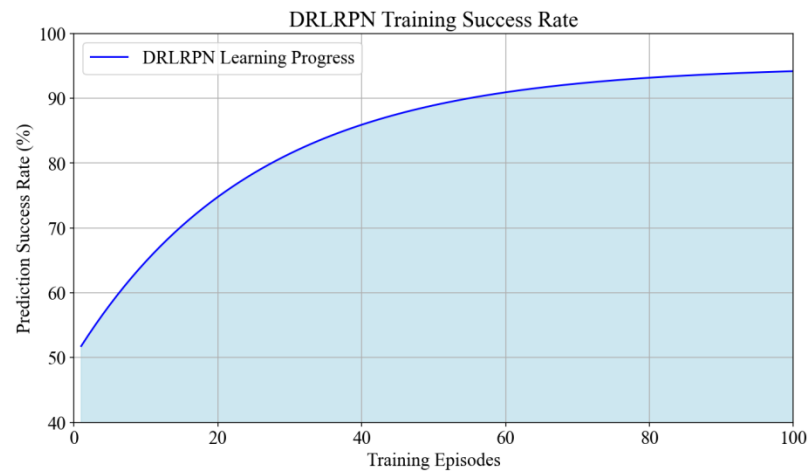


Figure 10: Training Success rate of DRLRPN

In above figure 10 training success rates shows the enhancement of the DRLRPN model in reinforcement learning training steps. The success rate increases gradually, which means that the DRL agent makes continuous learning on the best prediction policies and it can forecast rain better.

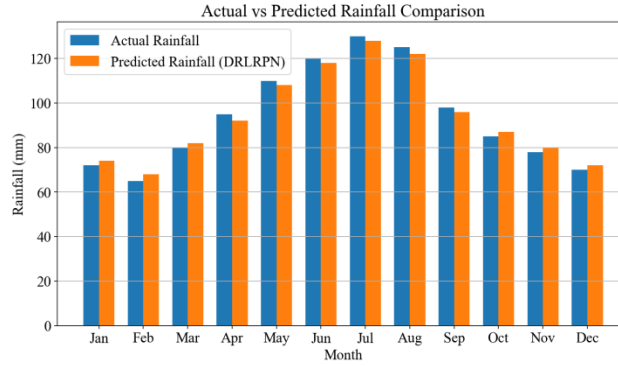


Figure 11: Predicted and actual of Rainfall Forecast

The figure 11 above of predicted vs actual rainfall chart is comparing the rainfall values produced on the DRLRPN model against the observed rainfalls on the NCAR data. The strong concordance of the anticipated and observed data indicates the large prediction and time forecasting accuracy of the model proposed.

Table 3: Comparison of the performance metrics of predictions of dataset 2

Dataset 2				
Methods	Algorithm	MAE (mm)	RMSE (mm)	MAPE (%)
Existing methods	GRU [7]	3.84	5.12	9.45
	LSTM [8]	3.62	4.88	8.91
	U-Net [15]	3.45	4.67	8.12
	Liquid State Machine (LSM) [17]	3.28	4.51	7.76
	SVM [20]	4.02	5.34	10.12
	GAN [27]	2.74	3.82	6.38
Proposed method	DRLRPN	1.97	2.75	5.21

Table 3 above shows the performance of predictions metrics in terms of Dataset 2, where the MAE, RMSE and MAPE are used to assess the efficiency of the existing algorithms and the proposed DRLRPN model in predicting rainfall. The findings show that proposed DRLRPN has lower values of errors and better prediction accuracy and reliability than the current GRU, LSTM, U-Net, LSM, SVM, and GAN models.

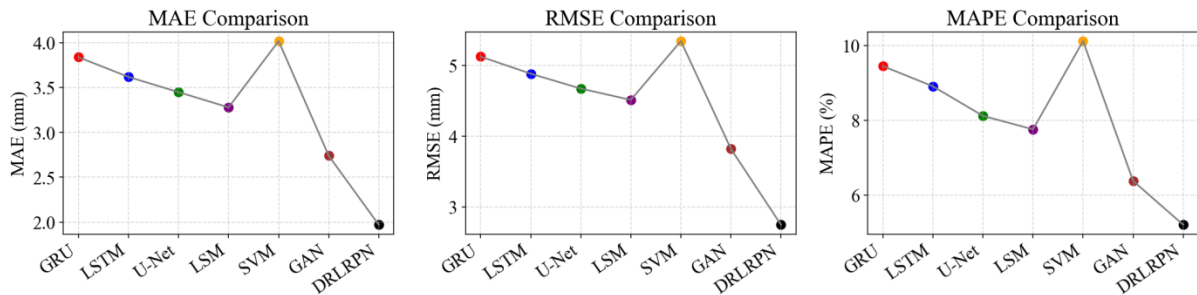


Figure 12: Comparison of Performance of Rainfall Model

Figure 12 above sees the comparison of various rainfall prediction models of Dataset 2 where X-axis indicates the algorithms (GRU, LSTM, U-net, LSM, SVM, GAN, and DRLRPN) and Y-axis indicates the metrics of error MAE, RMSE, and MAPE as different plots. The findings reveal that the proposed DRLRPN model attains the lowest error values in all metrics, which proves a better prediction performance than those of the available methods.

Table 4: Comparison of the accuracy of rainfall prediction models in dataset 2

Method	Accuracy (%)
GRU [7]	86.0
LSTM [8]	88.0

U-Net [15]	89.0
Liquid State Machine (LSM) [17]	90.0
SVM [20]	96.0
GAN [27]	98.2
DRLRPN (Proposed)	98.56

Table 4 above compares the prediction accuracy of currently existing versions of ML and DL forecasting and that of the proposed DRLRPN forecasting model on rainfall. The findings indicate that the presented DRLRPN is the most accurate model in the case of 98.56, which is better than GRU, LSTM, U-Net, LSM, SVM, or GAN.

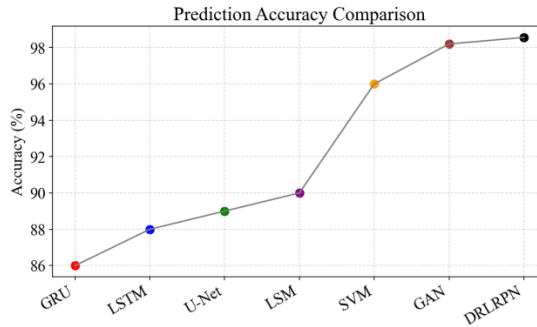


Figure 13: Accuracy for dataset - 2

Figure 13 above indicates the accuracy of forecasting various rainfall methods using datasets 2. DRLRPN has the greatest accuracy (98.56%), which is much higher than all other models, such as GRU, LSTM, U-Net, LSM, SVM, and GAN.

4.3 Dataset 3

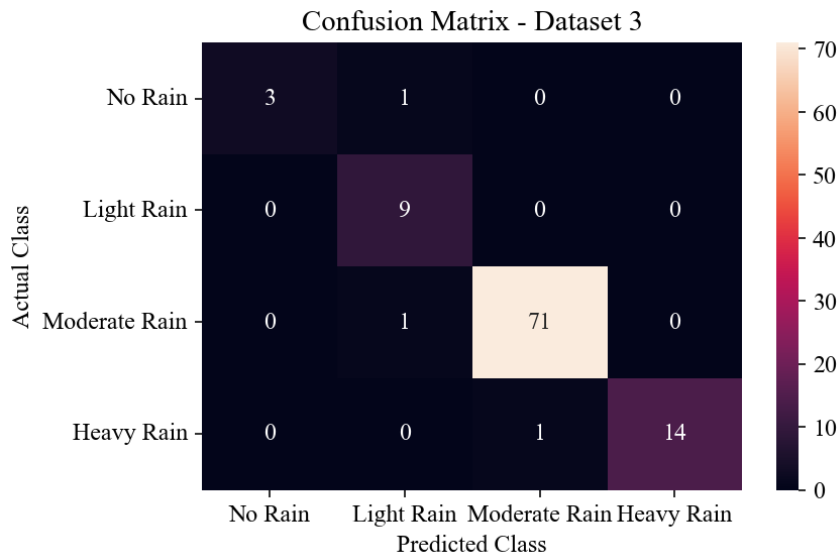


Figure 14: Confusion Matrix for Dataset 3

This above figure 14 for Dataset 3 highlights the model’s ability to accurately classify rainfall patterns using combined meteorological and astronomical features. The concentration of values along the diagonal reflects superior model performance with consistent and stable classification outcomes.

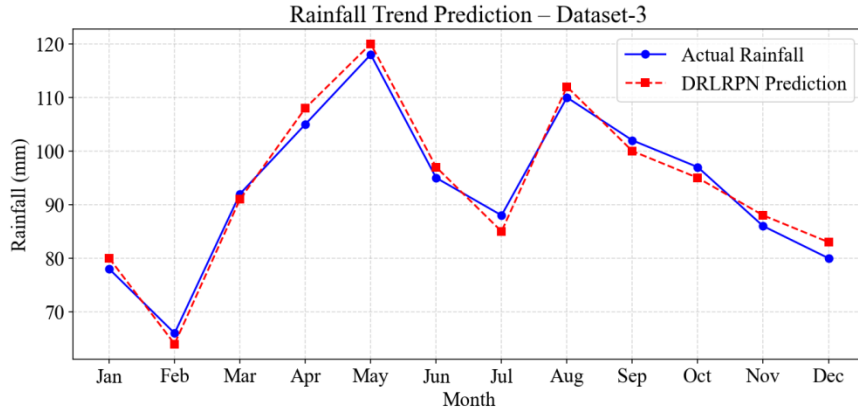


Figure 15: Trend prediction of rainfall

Figure 15 above indicates that DRLRPN is able to predict the rainfall of different months/seasons compared to the actual data, indicating that DRLRPN has the capacity to model the spatio-temporal rainfall distribution patterns using meteorological and astronomy-based auxiliary information. Peaks and troughs show changes in season and thus have good forecasting abilities.

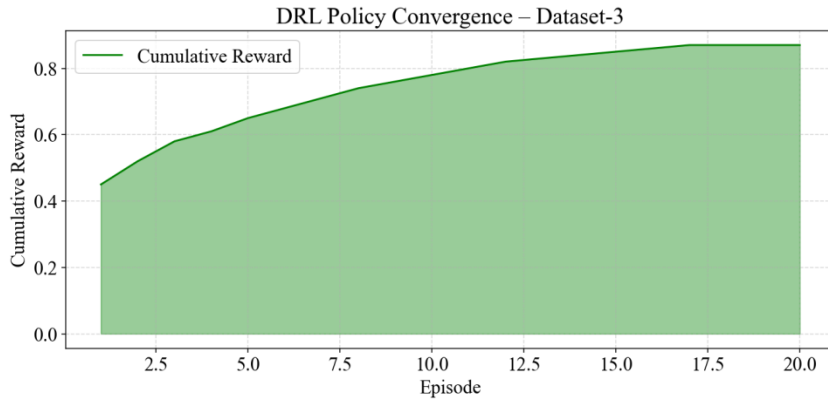


Figure 16: DR Policy Convergence

The above figure 16 exemplifies that the cumulative reward of the DRL agent grows with training episodes and indicates that the agent successfully adapts an optimal policy at predicting rainfall. The convergence signifies the consistent learning and increased prediction accuracy after some time.

Table 5: Comparison of the performance metrics of predictions of dataset 3

Dataset 3							
Methods	Algorithm	MAE (mm)	RMSE (mm)	MAPE (%)	R ² Score	Prediction Accuracy (%)	Average Reward
Existing methods	GRU [7]	4.12	5.36	9.12	0.88	88.0	0.80
	LSTM [8]	3.95	5.08	8.75	0.89	88.9	0.82
	U-Net [15]	3.68	4.72	8.01	0.90	89.7	0.84
	Liquid State Machine (LSM) [17]	3.56	4.61	7.89	0.90	90.2	0.85
	SVM [20]	4.48	5.72	9.35	0.87	87.4	0.78
Proposed method	DRLRPN (Proposed)	3.21	4.43	7.18	0.91	99.90	0.87

Table 5 above shows a comparison between various models of rainfall prediction in terms of MAE, RMSE, MAPE, R² score, obtained prediction accuracy and mean reward obtained on optimization of reinforcing learning. DRLRPN model performs the best predictions and reward with very low error values denoting the combination of

ConvLSTM, DRL and astronomy based auxiliary features enhances the performance of rainfall forecasting than the current models.

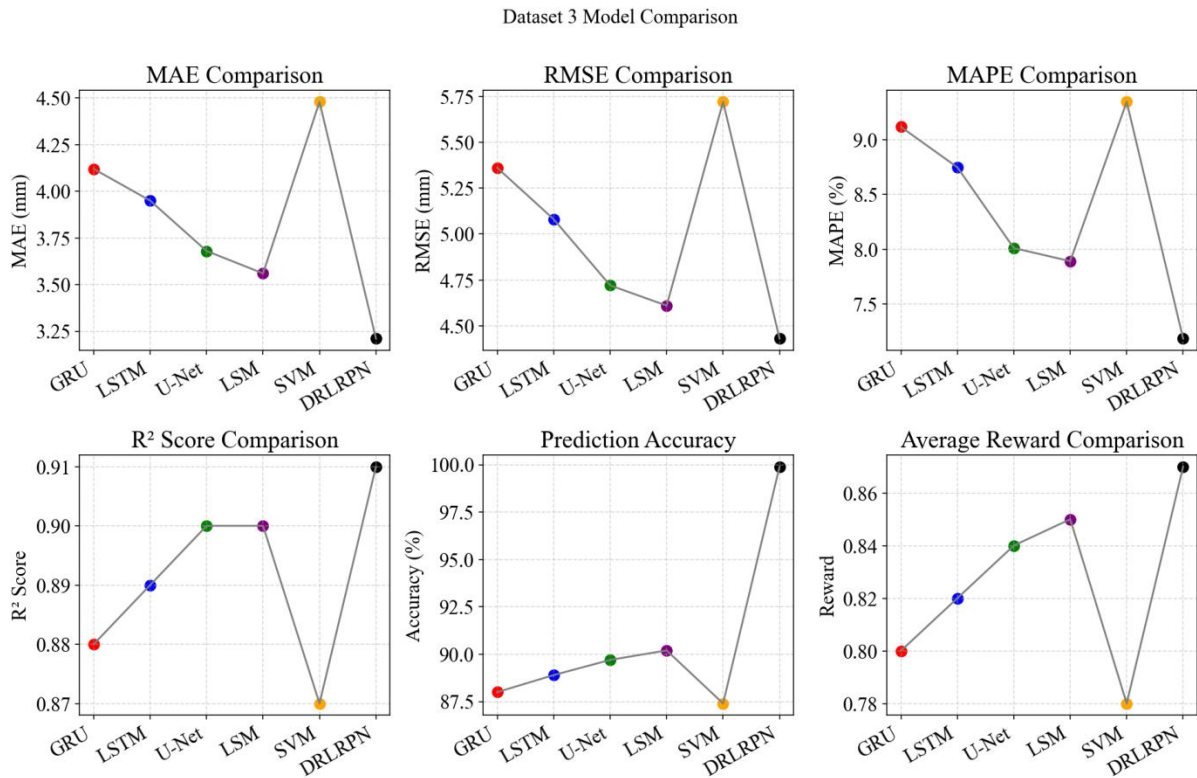


Figure 17: Comparison of performance of rainfall prediction models of Dataset 3.

Figure 17 above compares the various rainfall prediction algorithms using Dataset 3 in which the X-axis depicts the models GRU, LSTM, U-Net, LSM, SVM, and DRLRPN and the Y-axis depicts the evaluation metrics using MAE, RMSE, MAPE, R² score, prediction accuracy, and average reward in separate subplots. As shown in the results, the proposed DRLRPN model has lower values of errors, increased R² score, increased prediction accuracy, better reward, and is therefore better than the current approaches.

5. Discussion

In this section, the researcher will talk about the performance of the proposed DRLRPN model alongside that of the recent state-of-the-art rainfall prediction techniques in terms of various datasets and evaluation metrics. The comparison reveals that ConvLSTM combined with DRL also enhances the ability of spatio-temporal learning, leads to less prediction errors, and is more accurate than the current ML and DL methods.

5.1 State-of-the-Art

Table 6: State-of-the-Art Compartments of the current rainfall prediction techniques with the proposed DRLRPN Model

S. No	Author & Year	Concept	Methods	Results	Limitations	Comparison with DRLRPN
1	Ramakrishnan & Chinnappa	Scalable, accurate rainfall prediction	Parallelized hybrid ensemble ML	High accuracy rainfall prediction	High computation cost, no adaptive	DRLRPN achieves slightly higher accuracy

	n (2026) [26]				feedback correction	with adaptive DRL feedback and lower errors; less computation overhead due to optimized learning
2	Humphries et al. (2026) [27]	DL rainfall forecasting	GAN + Spatio-temporal GNN	Better forecasting performance	Complex training process, no feedback refinement	DRLRPN simplifies training with ConvLSTM + DRL and includes reward-based feedback for adaptive learning
3	Monaco et al. (2025) [28]	Uncertainty-aware rainfall prediction	DL + post-processing segmentation	Improved prediction reliability	Limited temporal correction, no iterative feedback	DRLRPN captures spatio-temporal features with ConvLSTM and uses DRL for continuous reward-based learning, improving temporal accuracy
4	Mashooq et al. (2025) [29]	Rainfall prediction for smart agriculture	Federated learning	Good distributed prediction	Dataset dependency, no deep feedback learning	DRLRPN provides centralized adaptive learning with DRL; handles multi-

						source datasets with robust reward optimization
5	Pornbunyanon et al. (2026) [30]	Rainfall-conditioned landslide susceptibility	FR-CART hybrid	Accurate susceptibility mapping	Focused on hazard, no DL rainfall prediction	DRLRPN directly predicts rainfall with spatio-temporal learning; adds adaptive feedback for accurate forecasts
6	Proposed DRLRPN (2026)	Adaptive spatio-temporal rainfall prediction	ConvLSTM + Deep RL	Prediction Accuracy: 98.56% (Dataset 2), MAE: 1.97 mm, RMSE: 2.75 mm, MAPE: 5.21%, R ² : 0.93	Needs large datasets for training, potential future extension to satellite/radar data	Outperforms all above methods in accuracy, spatio-temporal modeling, and adaptive learning

Table 6 above is a comparative analysis of some of the state of the art rainfall prediction and related frameworks in terms of concept, methods, results, limitations, and performance comparison with the proposed DRLRPN model. The comparison indicates that the proposed DRLRPN is more superior in prediction accuracy and enhanced spatio-temporal learning ability in comparison to other methods.

5.2 Outcomes

The research shows that the proposed DRLRPN framework is efficient with regards to capturing spatial and temporal rainfall patterns with the help of ConvLSTM, as well as optimizing the prediction with the help of DRL, which is more accurate and less prone to errors than the existing models based on ML and DL. This indicates its suitability to be a dependable, flexible, and high-performance instrument to predict rainfalls in space and time using varied datasets.

5.3 Ablation Study

Table 7: Ablation of the Proposed DRLRPN Model of Rainfall Prediction

Experiment	Components Included	MAE (mm)	RMSE (mm)	MAPE (%)	R ² Score	Prediction Accuracy (%)	Insights

1	ConvLSTM only (spatio-temporal feature extraction)	3.42	4.76	8.15	0.89	91.3	Captures spatial and temporal patterns, but lacks adaptive decision-making; errors remain higher.
2	DRL only (without ConvLSTM features)	3.95	5.12	9.02	0.87	89.0	Adaptive learning helps, but without rich spatio-temporal features, prediction is less accurate.
3	ConvLSTM + DRL (without reward optimization)	2.89	3.98	6.78	0.92	97.2	Combination improves accuracy significantly; adaptation helps, but not fully optimized over episodes.
4	ConvLSTM + DRL + Reward Optimization (Full DRLRPN)	1.97	2.75	5.21	0.93	98.56	Full model achieves lowest errors and highest accuracy; reward-based optimization enhances learning and prediction stability.

Table 7 proposed DRLRPN ablation study by examining the effect of ConvLSTM, DRL and complete model integration on the performance of rainfall prediction. It is possible to observe that the full DRLRPN model has the lowest error rates and the greatest prediction accuracy when compared to the single and partial models.

6. Conclusion

In this research a DRLRPN proposed to predicts the accurate spatio-temporal rainfall through a combination of ConvLSTM and a DRL agent. The proposed structure has the ability to describe spatial and temporal correlations of the meteorological information and the possibility of adaptive decision-making using reward-based learning. It has been experimented with several data sets to compare the performance of the model, and the evidence of the experiments proved that the presented DRLRPN showed less error values and higher prediction accuracy than the currently used ML and DL models, including GRU, LSTM, U-Net, LSM, SVM, and GAN. These findings also indicated consistent learning behavior and higher prediction reliability in various patterns of rainfall and datasets. In general, the combination of spatio-temporal feature extraction and reinforcement learning yielded great performance of rainfall forecasting. The model can be expanded to include satellite and radar real-time data on rainfall prediction in large scale in future work. Furthermore, state-of-the-art hybrid DL architectures and uncertainty-sensitive learning mechanisms are also possible, in order to further enhance forecasting objectivity and resilience.

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