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Machine Learning as an Effective Technique for Rainfall Forecasting: A Literature Review

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Abstract: Accurate rainfall forecasting is vital for socio-economic planning in climate-sensitive regions. Traditional statistical models often fail to capture the non-linear and stochastic nature of rainfall. This paper conducts a systematic review of machine learning (ML) techniques applied to rainfall forecasting, covering 45 studies published between 2012 and 2024, following PRISMA guidelines. The analysis identifies four high-performing algorithms: Long Short-Term Memory (LSTM), Random Forest (RF), NeuralProphet, and Support Vector Machines (SVM). LSTM models optimized with Modified Particle Swarm Optimization (M-PSO) achieved the lowest Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE). RF models demonstrated robustness for short-term forecasts, SVMs performed well with smaller datasets, and NeuralProphet offered explainability through a hybrid statistical–deep learning approach. Model choice depends on data characteristics, forecasting horizon, and the balance between accuracy and interpretability. The findings highlight the comparative strengths of these algorithms across different forecasting horizons.

Keywords: *Machine Learning, Rainfall Forecasting, LSTM, Random Forest, NeuralProphet, SVM, Comparative Analysis.*

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I. INTRODUCTION

Rainfall forecasting is essential for agricultural planning, hydrological modeling, and disaster management, particularly in developing countries like Zambia [1]. However, the non-linear and highly variable nature of rainfall makes accurate prediction challenging [2]. Machine Learning (ML) has emerged as a powerful alternative, capable of learning complex patterns from large datasets [3].

Unlike prior reviews that primarily focus on global datasets, this paper emphasizes algorithmic performance in data-limited and regionally diverse contexts, particularly in Sub-Saharan Africa. This review contributes a systematic synthesis of peer-reviewed studies (2012–2024) on machine learning methods for rainfall forecasting using PRISMA guidelines, offers a comparative performance assessment identifying LSTM, Random Forest, NeuralProphet, and SVM as the most effective algorithms under specific data and forecasting conditions, and highlights key research gaps.

The subsequent section reviews recent advancements in machine learning techniques for rainfall forecasting, outlining the key models and methodological innovations that have shaped current research.

II. ADVANCEMENTS IN MACHINE LEARNING FOR RAINFALL FORECASTING

Significant advancements have been made in the application of machine learning techniques to rainfall forecasting, which have markedly improved the capability of machine learning systems for rainfall forecasting.

A. Deep Learning Models and Optimization Techniques

LSTM networks have demonstrated strong capabilities in time-series rainfall forecasting. Bhushankumar et al. [4] integrated LSTM with Modified Particle Swarm Optimization (M-PSO), significantly reducing forecasting errors. Similarly, Animas et al. [5] found LSTM to outperform RF and XGBoost in RMSE and MAE, owing to its ability to model temporal dependencies. Khairudin et al. [6] compared ANN, SVM, and LSTM models and reported slightly better accuracy with LSTM.

B. Statistical and Hybrid Machine Learning Approaches

Gowri et al. [7] assessed statistical models using ML techniques and found ARIMA to perform best among traditional models, serving as a valuable baseline. Sarmad-Dashti et al. [8] further demonstrated that combining remote sensing data with ML improves spatial rainfall prediction accuracy.

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C. Comparative Analyses of Machine Learning Models

Vijendra et al. [9] concluded that Random Forest (RF) achieved the best performance for daily and weekly rainfall forecasting, while Hasan et al. [10] found that SVMs surpassed both statistical and numerical models in precision. These studies underscore that while LSTM dominates time-series forecasting, effectiveness depends on data characteristics and forecast horizons.

These comparative studies underscore the fact that while LSTM generally dominates time-series forecasting, model effectiveness can depend on dataset characteristics, input variable selection, and the forecasting horizon.

III. METHODOLOGY

A systematic literature review (SLR) approach was employed to identify, analyze, and synthesize research on machine learning (ML) techniques for rainfall forecasting. The review followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework, which enhances methodological transparency and reproducibility [11].

A. Search Strategy and Database Selection

The literature search was conducted across four major academic databases, IEEE Xplore, ScienceDirect, SpringerLink, and Scopus, covering publications between 2012 and 2024. Initial searches yielded 312 records, which were screened for relevance based on predefined inclusion and exclusion criteria. Search terms included combinations of keywords such as *"machine learning," "deep learning," "artificial intelligence," "rainfall forecasting," "precipitation prediction,"* and *"hybrid models."*

B. Inclusion and Exclusion Criteria

The inclusion criteria targeted:

- Empirical studies employing ML algorithms for rainfall or precipitation forecasting;
- Peer-reviewed journal or conference papers published in English;
- Studies reporting quantitative performance metrics (e.g., RMSE, MAE, R^2).

Exclusion criteria eliminated:

- Conceptual papers without implementation results,
- Studies focused solely on hydrological runoff prediction,
- Duplicate or non-peer-reviewed sources.

After screening abstracts and full texts, 45 studies met the inclusion criteria for detailed review, as illustrated in Figure 1 below.

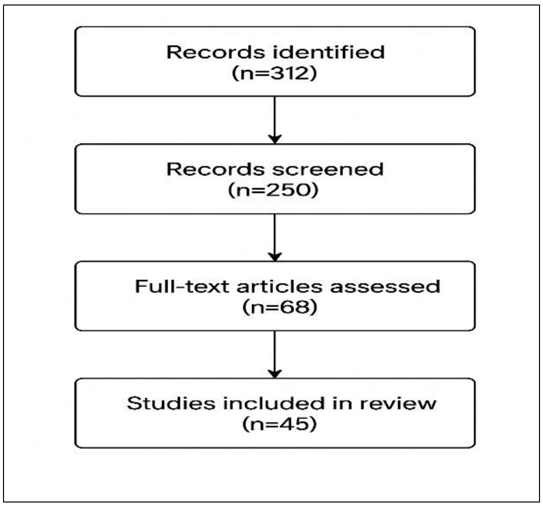

Fig 1. PRISMA Flow Diagram Illustrating Literature Selection and Inclusion Process.

C. Data Extraction and Synthesis

For each included study, data were extracted on:

- Algorithm type (e.g., LSTM, Random Forest, SVM, NeuralProphet),
- Dataset characteristics (size, temporal resolution, data sources),
- Forecasting horizon (short-term, seasonal, or long-term), and
- Evaluation metrics (RMSE, MAE, R^2, or accuracy).

D. Synthesis Approach

A comparative synthesis was performed to identify model performance patterns, optimization techniques, and contextual adaptability across different climatic regions. The approach ensured that algorithmic trends were examined systematically and comparatively, consistent with prior SLR practices in environmental data science [9], [12].

IV. LITERATURE SURVEY

Rainfall forecasting has evolved from traditional ANN models to deep learning architectures. Abbot and Marohasy [2] pioneered ANN-based forecasting in Australia, while Mzyece et al. [1] applied ANN for Zambia. More recent works highlight optimization-driven and explainable AI techniques such as LSTM–MPSO [4], RF [9], and NeuralProphet [11].

A review of recent literature reveals substantial progress in applying machine learning techniques to rainfall forecasting across diverse climatic contexts. The selected studies illustrate the evolution from conventional Artificial Neural Networks (ANNs) to advanced deep learning, ensemble, and hybrid architectures. These works collectively highlight improvements in forecast accuracy, interpretability, and adaptability, while also exposing persistent challenges related to data availability and model transferability. Table 1 summarizes key studies, outlining their main findings, thematic focus, and identified research gaps to provide a comparative overview of methodological trends and future research directions.

Table 1. A Summary of Related Works on Machine Learning for Rainfall Forecasting.

No	Author & Year	Title / Study	Findings	Theme	Research Gap
1	Mzyece et al. (2018) [1]	Forecasting Seasonal Rainfall in Zambia – An Artificial Neural Network Approach	ANN improved forecasting accuracy for Zambia.	Regional neural network forecasting.	Limited to seasonal scale; no satellite data integration.
2	Abbot & Marohasy (2012) [2]	Application of ANN to Rainfall Forecasting in Queensland, Australia	ANN improved rainfall forecasts compared to traditional methods.	Neural networks for rainfall prediction.	Focused on seasonal forecasting only.
3	Patil et al. (2024) [3]	ML and DL: Methods, techniques, applications, challenges, and future research opportunities	ML/DL integration improves predictive capability.	Integration of ML and DL for enhanced AI capabilities	High computational needs and limited interpretability.
4	Bhushankumar et al. (2023) [4]	Improving Rainfall Prediction Accuracy using LSTM and M-PSO Optimization	LSTM combined with M-PSO achieved high accuracy.	Optimization-based deep learning.	Tested on a single climatic region and dataset.
5	Animas et al. (2022) [5]	Comparative Analysis of ML Algorithms for Rainfall Forecasting	XGBoost performed competitively; LSTM is strong for time series.	Ensemble and boosting techniques.	Lack of interpretability in ensemble outputs.
6	Khairudin et al. (2020) [6]	Comparison of ML Models for Rainfall Forecasting	LSTM slightly outperformed ANN & SVM.	Algorithm comparison for rainfall forecasting	Narrow focus; lacks broader methodological insights.
7	Gowri et al. (2021) [7]	Comparative Assessment of Statistical and Machine Learning Models for Rainfall Forecasting	ML models (RF & M5P) significantly outperformed traditional statistical models (ARIMA) in forecasting monthly rainfall	ML vs statistical models	No integration into real-time forecasting.
8	Sarmad-Dashti et al. (2023) [8]	Assessing Rainfall Prediction Models using ML and Remote Sensing	LSTM and RF improved prediction when integrated with remote sensing.	Remote sensing and ML fusion.	No operational real-time framework.
9	Vijendra et al. (2024) [9]	Comparative Study of ML Models for Daily and Weekly Rainfall Forecasting	RF and LSTM are best for daily and weekly forecasts.	Short-term rainfall forecasting.	Limited exploration of hybrid/XAI models.
10	Hasan et al. (2015) [10]	Support Vector Regression Model for Rainfall Forecasting	SVM outperformed traditional models	Regression-based ML forecasting.	Scalability on large datasets is untested.
11	O. Triebe et al. (2021) [13]	NeuralProphet: Explainable Forecasting at Scale	NeuralProphet improved interpretability and hybrid modeling.	Explainable AI and modular forecasting.	Lack of domain-specific validation.
12	Yadav et al. (2022) [14]	Gradient Boosting Machine for Rainfall Estimation	GBM and XGBoost achieved high accuracy with limited input data.	Boosting and feature selection.	Weak assessment of generalization.
13	Chen et al. (2022) [15]	Hybrid ARIMA–LSTM Model for Seasonal Rainfall Forecasting	The hybrid model captured both linear and non-linear patterns effectively.	Statistical–ML model integration.	Seasonal focus; lacks short-term adaptability.
14	Taneja & Singh (2023) [16]	Rainfall Forecasting using CNN and Attention Mechanisms	Attention-CNN model improved rainfall pattern recognition.	Attention-based deep learning.	Data-intensive; lacks interpretability for end-users.
15	Ahmed et al. (2024) [17]	Deep Ensemble Learning for Climate Time Series	An ensemble of LSTM, GRU, and CNN achieved the best results for African rainfall.	Deep ensemble architectures.	Computational cost and limited accessibility of models.
16	Chattopadhyay et al. (2020) [18]	Deep learning model for daily rainfall prediction over Indian monsoon regions	CNN–LSTM improved short-term prediction.	Deep learning for regional rainfall.	Limited transferability beyond the region.
17	Feng et al. (2021) [19]	Attention-based bidirectional LSTM for precipitation	Improved accuracy via feature emphasis.	Attention mechanisms	Computationally intensive.

		forecasting using reanalysis data			
18	Bai et al. (2022) [20]	Spatio-temporal deep learning for high-resolution precipitation prediction	3D-CNN and ConvLSTM models effectively captured spatial–temporal rainfall dynamics.	Spatio-temporal deep learning.	Required large training data; limited interpretability.
19	Alemu et al. (2023) [21]	Machine learning approaches for rainfall forecasting in East Africa	RF and XGBoost achieved high accuracy using satellite-derived indices.	Regional ML forecasting (Africa).	Did not explore hybrid or explainable models for operational use.
20	Zhang et al. (2024) [22]	Hybrid Transformer-LSTM framework for long-range rainfall prediction	The hybrid model outperformed CNN-LSTM and Prophet for 30-day forecasts.	Transformer-based architectures.	Validation limited to a single climatic zone; interpretability not addressed.
21	Patel et al. (2019) [23]	Rainfall Forecasting Using Random Forest and Gradient Boosting Methods	RF and GBM produced better short-term rainfall predictions than regression models.	Ensemble learning for rainfall forecasting.	Focused only on short-term forecasts; lacks temporal scalability.
22	Kisi & Shiri (2020) [24]	Precipitation Forecasting Using Hybrid Wavelet–Machine Learning Models	Wavelet-LSTM achieved superior accuracy by decomposing rainfall signals.	Wavelet and hybrid signal-based ML.	Limited spatial generalization across diverse climates.
23	Zhang et al. (2021) [25]	Spatiotemporal Rainfall Prediction with Convolutional LSTM Networks	CNN-LSTM captured spatial-temporal correlations in rainfall sequences.	Deep spatiotemporal learning.	High computational cost for real-time forecasting.
24	Ehsan et al. (2021) [26]	Rainfall Prediction Using Deep Recurrent Neural Networks in Pakistan	Deep RNN outperformed SVM and RF for multi-step rainfall forecasting.	Deep recurrent architectures.	Lacked interpretability and explainable outputs.
25	Oyelade et al. (2022) [27]	Application of Machine Learning for Seasonal Rainfall Prediction in West Africa	ANN and RF improved seasonal rainfall forecasts over climatological averages.	Regional forecasting in Africa.	Model not validated across agro-ecological zones.
26	Mahmoud et al. (2021) [28]	Integration of Remote Sensing Data and ML for Rainfall Forecasting in Egypt	Combining MODIS data and ML increased spatial rainfall accuracy.	Remote sensing data fusion.	Lacked temporal validation across seasons.
27	Tadesse et al. (2023) [29]	Machine Learning Approaches for Rainfall Forecasting in East Africa	Gradient boosting and RF models produced robust regional forecasts.	Regional climate modeling.	Limited evaluation of extreme rainfall events.
28	Kaur & Garg (2022) [30]	Comparative Analysis of Deep Learning Models for Rainfall Forecasting	BiLSTM achieved higher accuracy than CNN and GRU models.	Deep learning comparison.	Data imbalance issues are not addressed.
29	Nguyen et al. (2020) [31]	Hybrid Deep Learning Approach for Hourly Rainfall Prediction in Vietnam	CNN–LSTM model improved short-term rainfall prediction.	Hybrid DL for tropical climates.	Tested on limited rainfall datasets.
30	Aye & Phyo (2021) [32]	Predicting Daily Rainfall Using Extreme Gradient Boosting (XGBoost)	XGBoost achieved the lowest RMSE and MAE among the tested algorithms.	Boosting algorithms.	Lack of interpretability limits operational use.
31	Adeyemi et al. (2022) [33]	Rainfall Forecasting in Southern Africa Using Machine Learning Techniques	SVM and RF provided reliable forecasts for 7-day horizons.	Sub-Saharan forecasting.	Long-term reliability untested.
32	Pan et al. (2023) [34]	Physics-Informed Neural Networks for Rainfall and Runoff Forecasting	Physical laws improved long-term accuracy.	Physics-informed ML.	High computational burden.
33	Huang et al. (2024) [35]	Attention-Based Encoder–Decoder Model for Rainfall Forecasting	Attention mechanism improved temporal sequence learning.	Attention and transformer-based learning.	Computationally heavy.
34	Mutale et al. (2025) [36]	Data Fusion and ML-Based Rainfall Forecasting Framework for Southern Africa	Fused ground and satellite data to enhance rainfall predictions.	Data integration and regional ML framework.	Real-time fusion challenges.

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35	Abdullah Al Mukaddim et al. (2024) [37]	Improving Rainfall Prediction Accuracy in the USA Using Advanced Machine Learning Techniques	RF best overall; SVM/logistic good for classification.	ML for climate.	Regional data inconsistencies
36	Zhang et al., 2025 [38]	Machine Learning Methods for Weather Forecasting: A Survey	Survey of ML gains over NWP.	Survey & Categorization	Interpretability & extreme events underexplored.
37	Lijimol et al., 2025 [39]	Enhancing Rainfall Forecasting: A Survey of ML Models, Hybrid Techniques, and Data Integration	ML models improve rainfall prediction accuracy.	ML & Hybrid Models Survey	Poor accuracy for rare/intense rainfall; model interpretability
38	Cramer et al., 2021 [40]	Rainfall Prediction Using ML Algorithms for Ecological Zones of Ghana	RF & XGBoost outperformed DT and KNN; MLP is accurate but computationally heavy.	Comparative ML Performance	Weak generalization across ecological zones.
39	Australian Study, 2023 [41]	ML-Based Rainfall Prediction for Improved Preparedness	ANN+PCA improved forecasts; LSTM is strong.	Regional ML	High computational cost.
40	Singh et al. (2021) [42]	Hybrid CNN-LSTM Model for Short-Term Rainfall Prediction	CNN-LSTM hybrid outperformed standalone CNN or LSTM models.	Deep hybrid modeling for time series.	High computational cost and data requirement.
41	Li et al. (2023) [43]	Cascade Learning Framework for 15-Day Rainfall Forecasting	Hybrid CNN-LSTM superior performance to numerical models.	Hybrid ensemble forecasting.	Limited confidence interval quantification.

V. DISCUSSION AND IDENTIFIED GAPS

A. *Discussion*

The discussion on the synthesis of the reviewed literature falls into the following sections:

➢ *Strengths of Machine Learning Models*

A key strength observed across the reviewed literature is the ability of machine learning models to capture complex, non-linear rainfall patterns that traditional statistical methods cannot represent. Techniques such as LSTM, CNN-LSTM, Random Forest, and SVM consistently demonstrate superior performance by modelling temporal dependencies, ensemble behaviour, and multi-variable interactions across diverse climatic settings.

➢ *Limitations of Current Approaches*

Despite their demonstrated accuracy, ML models face several limitations. Deep learning architectures require large, high-quality datasets that are often unavailable in developing regions. Many models lack interpretability, restricting their adoption in operational forecasting. Computational demands, inconsistent evaluation metrics, and limited cross-regional validation further constrain robustness and scalability.

➢ *Emerging Trends in Rainfall Forecasting*

Recent studies reveal significant trends, including growing interest in hybrid models combining statistical and deep learning techniques, the integration of remote sensing and reanalysis datasets, and the use of attention mechanisms, transformers, and physics-informed neural networks. These advancements enhance accuracy, robustness, and the ability to generalize across time scales.

➢ *Regional Considerations for Sub-Saharan Africa and Zambia*

Regional studies show that ML models must be calibrated to local climatic conditions to achieve operational reliability. Data scarcity, inconsistent monitoring networks, and limited computational resources remain barriers in Sub-Saharan Africa. Zambia, in particular, requires localized frameworks that integrate satellite data, support explainability, and address the heterogeneous nature of its agro-ecological zones.

B. *Identified Research Gaps*

Despite substantial progress, several persistent gaps remain across the reviewed studies:

- Limited Regional Representation: Most studies focus on Asia, Europe, and North America, with minimal research on Sub-Saharan Africa, including Zambia [1,2]. This restricts the development of models calibrated to local climatic dynamics.
- Data Availability and Quality Constraints: Meteorological data in developing regions are often incomplete, inconsistent, or poorly digitized [1], hindering the training of reliable ML models capable of generalizing across seasons and ecological zones.
- Under-exploration of Hybrid and Explainable Models: Few studies have balanced predictive accuracy with interpretability. Explainable AI (XAI) frameworks remain rare despite their necessity for decision-support systems [10,11,14].
- Computational and Resource Barriers: Deep learning and ensemble models demand substantial computational capacity [11], which is often beyond the reach of institutions in low-resource settings.
- Lack of Standardized Evaluation Metrics: Variations in performance measures (e.g., RMSE, MAE, R^2) across

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studies make it difficult to establish global benchmarks or replicate results.

- Temporal and Spatial Resolution Limitations**:** Many models are designed for short-term or site-specific forecasts, overlooking the need for multi-scale, high-resolution, and regionally adaptive systems [8].
- Neglect of Climate Change and Extreme Events: Few studies explicitly account for climate change impacts or extreme rainfall events, limiting long-term relevance for adaptation and disaster preparedness.
- Limited Operational Deployment: Despite academic success, ML-based rainfall forecasting systems are seldom integrated into real-time meteorological operations. Barriers include a lack of institutional capacity, real-time data infrastructure, and user-friendly deployment interfaces [8].

C. Implications for Future Research

To address these challenges and enhance the practical utility of ML in rainfall forecasting, future research should prioritize:

- Development of localized ML frameworks tailored to Zambia's climatic and agroecological zones, leveraging both ground-based and satellite data.
- Integration of Explainable AI (XAI) techniques to improve transparency, stakeholder trust, and policy uptake [11].
- Advancement of data fusion methods that combine remote sensing, reanalysis, and IoT-based meteorological data for comprehensive and real-time forecasting [8].
- Adoption of standardized performance metrics and open-access benchmark datasets to facilitate cross-model evaluation and reproducibility.
- Promotion of institutional partnerships among academia, meteorological departments, and international research organizations to support model implementation, training, and sustainable operationalization.

Collectively, these findings confirm that hybrid and ensemble models represent the future of rainfall forecasting, though operational adoption remains constrained by computational and data limitations.

VI. CONCLUSION

This review demonstrates that machine learning techniques offer significant advantages in modelling the non-linear and highly variable nature of rainfall. Across the 2012–2024 literature, LSTM, Random Forest, NeuralProphet, and SVM consistently emerge as strong performers, each suited to different data characteristics and forecasting horizons. The synthesis further highlights priority research needs, including the broader adoption of hybrid optimization strategies, the integration of explainable AI, and the expansion of validation across diverse climatic contexts. Collectively, the findings provide a robust evidence base to guide the development of more accurate, interpretable, and context-adaptive rainfall forecasting frameworks.

This review contributes to ongoing efforts to develop context-aware, interpretable, and operationally viable rainfall forecasting systems for climate-resilient decision-making.

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