Jurnal
Teknologi

Full Paper

ADVANCES IN MACHINE LEARNING-BASED RAINFALL FORECASTING: A SYSTEMATIC REVIEW

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Article history
Received
16 December 2024
Received in revised form
3 June 2025
Accepted
3 June 2025
Published Online
27 February 2026

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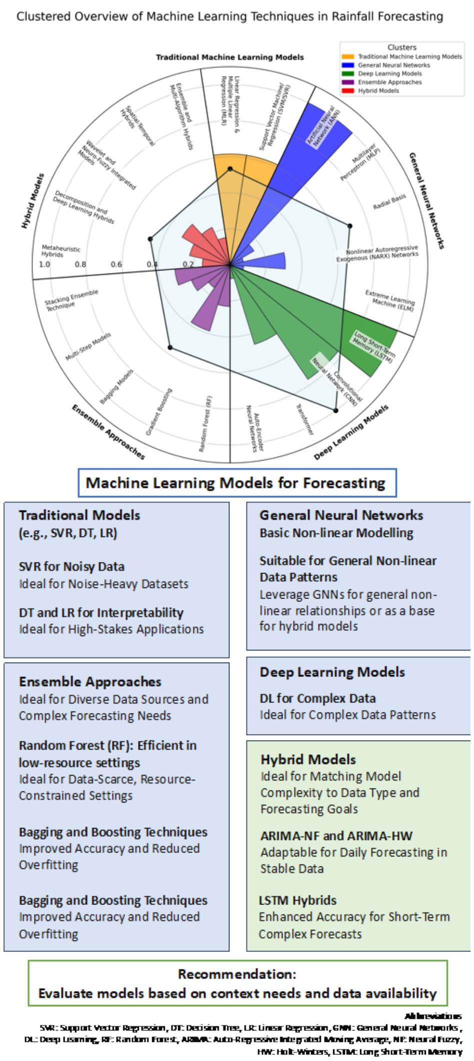
Graphical abstract



Abstract

Rainfall forecasting plays a critical role in managing water resources, reducing the risks of extreme weather, and supporting agriculture. Traditional methods such as Numerical Weather Prediction (NWP) and statistical models often struggle with accuracy and scalability, especially when dealing with localized weather conditions or extreme events. In recent years, machine learning (ML) has emerged as a powerful tool for identifying complex patterns in meteorological data. This review explores the progress of ML-based rainfall forecasting from 2014 to 2024. It organizes the literature into five main groups: Traditional Machine Learning models, General Neural Networks, Deep Learning models like LSTM and CNN, Ensemble techniques, and Hybrid models. The paper also highlights key trends through an N-gram analysis of publications from Scopus and Web of Science. The main contributions of this review include an overview of model development over the last decade, a comparison of model performance across different forecasting scenarios, and a summary of which models are best suited for various data environments. While ML models show strong potential, they also face ongoing challenges such as overfitting, high computational costs, and limited interpretability. This review concludes by identifying future research directions to improve the efficiency, transparency, and real-world applicability of ML-based rainfall forecasting.

Keywords: Rainfall forecasting, machine learning, deep learning, hybrid models, temporal-spatial dependencies

Abstrak

Ramalan hujan memainkan peranan penting dalam pengurusan sumber air, pengurangan risiko cuaca ekstrem, dan menyokong sektor pertanian. Kaedah tradisional seperti Ramalan Cuaca Berangka (NWP) dan model statistik sering menghadapi kekangan dari segi ketepatan dan kebolehsuaian, terutamanya dalam menangani keadaan cuaca setempat atau kejadian ekstrem. Dalam beberapa tahun kebelakangan ini, pembelajaran mesin (ML) telah muncul sebagai kaedah berkesan untuk mengenal pasti corak meteorologi yang kompleks. Kajian ini meneroka kemajuan dalam ramalan hujan berasaskan ML dari tahun 2014 hingga 2024. Ia mengkategorikan kajian terdahulu kepada lima kumpulan utama: model ML Tradisional, Rangkaian Neural Umum, model Pembelajaran Mendalam seperti LSTM dan CNN, teknik Ensemble, dan model Hibrid. Kajian ini turut mengetengahkan tren utama berdasarkan analisis N-gram terhadap penerbitan daripada Scopus dan Web of Science. Sumbangan utama kajian ini termasuk gambaran menyeluruh tentang perkembangan model dalam tempoh sepuluh tahun terakhir, perbandingan prestasi model mengikut senario ramalan, serta rumusan tentang kesesuaian model bagi pelbagai jenis data. Walaupun model ML menunjukkan potensi yang besar, cabaran seperti overfitting, keperluan pengkomputeran tinggi, dan kekurangan kebolehfahaman masih perlu ditangani. Kajian ini mengakhiri dengan mengenal pasti arah tuju penyelidikan masa depan untuk meningkatkan kecekapan, ketelusan, dan kebolehlaksanaan sebenar bagi ramalan hujan berasaskan ML.

Kata kunci: Ramalan hujan, pembelajaran mesin, pembelajaran mendalam, model hibrid, kebergantungan temporal-spatial

1.0 INTRODUCTION

Accurate and reliable rainfall forecasting is essential for managing water resources, mitigating the impacts of extreme weather events, and supporting agricultural productivity. Conventional forecasting methods, often based on physical models such as Numerical Weather Prediction (NWP) model, have achieved varying degrees of success. However, these methods are sometimes constrained by the inherent complexities of atmospheric processes, the challenges of capturing localized weather phenomena, and the significant computational resources required for high-resolution forecasts [1], [2].

In addition to physical models, statistical methods have been widely employed in rainfall forecasting due to their simplicity and efficiency. These methods are particularly suitable for short-term and site-specific forecasts, as they are less computationally demanding. However, they may not fully capture the underlying physical processes governing rainfall and can be less accurate during extreme weather events or in regions with limited data availability. Despite these limitations, statistical and physical-based methods are often used in a complementary manner, with each providing unique advantages [3]–[5].

The advent of machine learning (ML) has opened new avenues for enhancing rainfall forecasting by harnessing large datasets and uncovering complex patterns that traditional models might overlook. ML-based approaches offer the potential to complement or even surpass conventional methods in certain scenarios, providing more flexible, data-driven models capable of adapting to the nonlinearities and uncertainties in weather systems [6]–[8]. These approaches can bridge the gap between physical-based and statistical methods, leveraging the strengths of both.

However, despite the increasing number of studies using machine learning for rainfall forecasting, several gaps remain. Many existing reviews do not offer a detailed comparison between traditional and deep learning models across different forecasting scenarios. There is also limited discussion on model performance in data-scarce regions, challenges in real-world deployment, and how to balance accuracy with interpretability and computational cost.

This systematic review aims to provide a comprehensive overview of the advances in machine learning-based rainfall forecasting. We will provide an overview of the current state of machine learning-based rainfall forecasting techniques and examine the emerging trends in ML-based methods. Following this, we will explore various machine learning techniques applied in this domain, including deep learning models, ensemble methods, and hybrid approaches that integrate machine learning with traditional forecasting techniques. Additionally, we will discuss the challenges and limitations of current ML models, such as data quality, model interpretability, and the need for robust validation frameworks. The objectives of this review are as follows:

1. To identify machine learning techniques used for rainfall forecasting in the latest 10 years of literature. (2014-2024)
2. To assess the effectiveness of different machine learning models in rainfall forecasting by reviewing their methodologies, data types, and performance metrics.
3. To identify gaps and limitations in current research to identify areas for future investigation in machine learning-based rainfall forecasting.

By synthesizing the current state of research, this review seeks to identify key trends, gaps, and future directions in ML-based rainfall forecasting. The ultimate goal is to provide insights that can guide researchers and practitioners in developing more accurate, reliable, and scalable forecasting models.

2.0 REVIEW PAPER METHODOLOGY

The review paper focuses on articles related to rainfall forecasting using machine learning techniques. The research process involved a systematic search across multiple academic databases, specifically Scopus and Web of Science (WoS). Although IEEE Explorer was initially included in the search strategy, it did not yield any relevant results due to the syntax used, leading to its exclusion from further review.

The search strategy, as outlined in Figure 1, was designed to capture a comprehensive range of studies. It employed English and syntax aimed at identifying articles published between 2014 and 2024, written in English, and focusing on rainfall or precipitation forecasting. The methods considered include quantitative, statistical, data analysis, or numerical approaches involving machine learning, deep learning, artificial intelligence, or neural networks.

Inclusion and exclusion criteria were systematically applied throughout the article selection process. Initially, papers were filtered based on their titles and abstracts, focusing specifically on those addressing rainfall forecasting using machine learning techniques. Studies that directly discussed rainfall or precipitation forecasting using machine learning, deep learning, or artificial intelligence were included. Conversely, papers on topics unrelated to direct rainfall forecasting—such as runoff forecasting, streamflow prediction, landslides, bias correction, statistical downscaling, and other hydrological phenomena—were excluded. Review papers were also omitted to ensure the focus remained on original research articles.

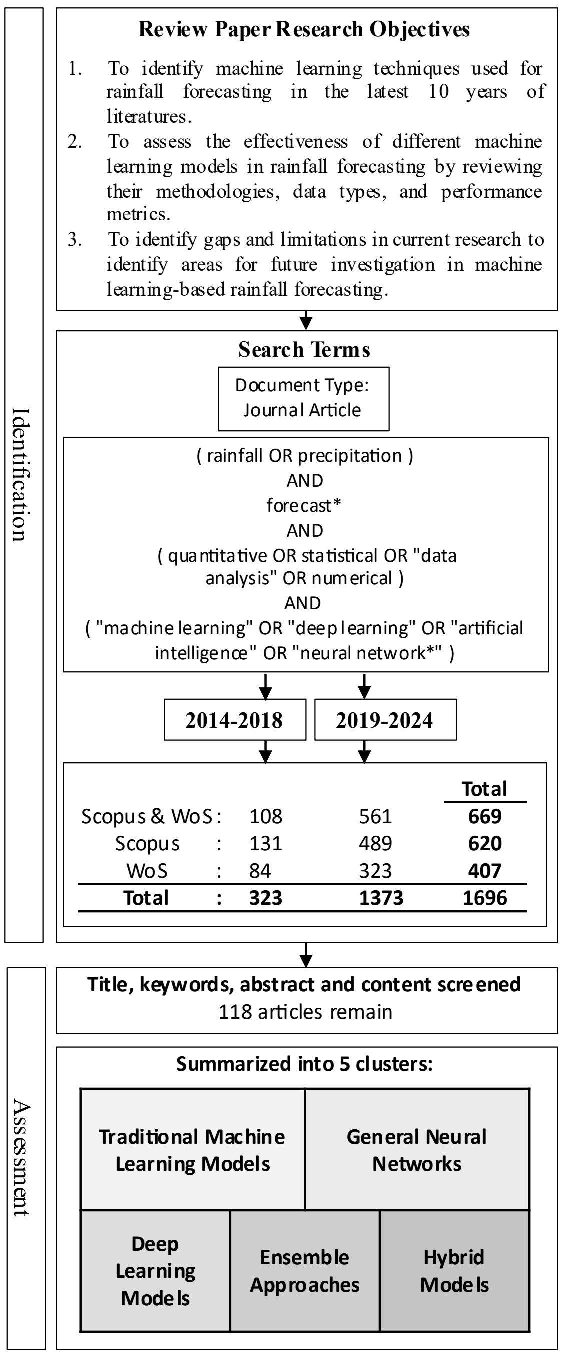


Figure 1 Overview of the systematic review process for rainfall forecasting methods, including the research objectives, literature search strategy, article selection criteria, and data analysis framework

To examine trends and developments in rainfall forecasting methodologies, the selected literature was divided into two distinct timeframes: January 1, 2014, to December 31, 2018, and January 1, 2019, to September 1, 2024. This segmentation facilitated a comparative analysis of how machine learning applications in rainfall forecasting have evolved over the past decade. By comparing these two periods, the review highlights advancements in methodologies, identifies emerging trends, and uncovers potential gaps in current research practices.

Following the article selection, detailed information was extracted from each study. This included data types used, machine learning models applied, performance metrics employed, and key findings related to rainfall forecasting. During this synthesis, recurring patterns and similarities in rainfall forecasting methodologies were observed, prompting the classification of the literature into four distinct clusters: (1) Traditional Machine Learning Models, (2) General Neural Networks, (3) Deep Learning Models, (4) Ensemble Approaches and (5) Hybrid Models (refer Figure 1). Throughout the data extraction and review process, efforts were made to select the most recent papers, especially when multiple studies exhibited redundancy. In such cases, the most relevant and recent paper was chosen to ensure that the review captures the latest advances in the field. This approach provides a comprehensive overview of the current landscape of machine learning-based rainfall forecasting and offers valuable insights into future research directions.

3.0 OVERVIEW ANALYSIS

The analysis of machine learning-based rainfall forecasting methods from 2014 to 2024 reveals significant shifts and trends in the field. An N-gram analysis, a text mining technique used to identify and quantify the occurrence of specific terms or sequences of words in the literature, was employed to highlight key methods and approaches used in rainfall forecasting research. Referring to Figure 2, the N-gram analysis showcases the top 25 terms extracted from research articles in Scopus and Web of Science, indicating an evolution in the adoption of various machine learning models over time.

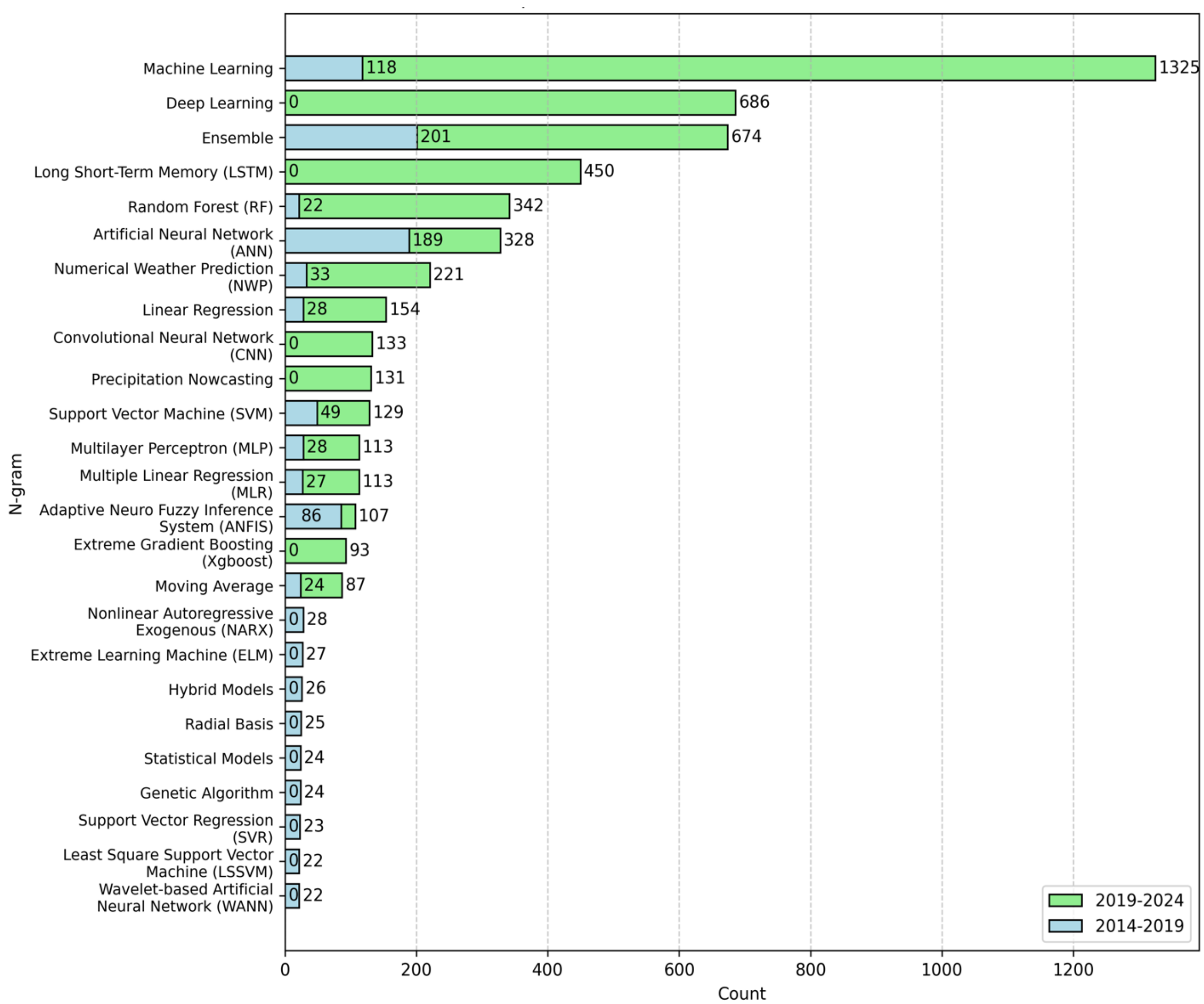


Figure 2 Top 25 N-grams from article papers on machine learning-based rainfall forecasting in Scopus and Web of Science, comparing 2014–2019 and 2019–2024

The radar chart in Figure 3 provides a comprehensive overview of machine learning techniques in rainfall forecasting, normalized across five key clusters: Traditional Machine Learning Models, General Neural Networks, Deep Learning Models, Ensemble Approaches, and Hybrid Models. The outer line plot highlights the relative prevalence of each cluster, with Deep Learning Models and Ensemble Approaches showing the highest normalized representation, indicating their strong focus in recent studies. The prominence of Ensemble Approaches also reflects the growing trend of combining multiple models to enhance forecasting accuracy, which has gained significant attention in recent years. This growth reflects the increasing ability of deep learning to model spatiotemporal dependencies, and the reliability of ensemble approaches in combining model strengths to improve robustness.

The inner radial bars display the normalized paper counts for specific methods within each cluster, offering a deeper dive into the popularity of individual techniques. Notably, Long Short-Term Memory (LSTM) and Random Forest (RF) stand out as the most frequently discussed methods. LSTM has gained popularity due to its unique ability to capture long-term dependencies in sequential rainfall and climate time series, making it ideal for monsoon and seasonal forecasting applications. RF, dominating the Ensemble Approaches cluster, has become a widely used model for its robustness, ease of use, and strong performance in noisy or incomplete datasets. Its ability to reduce overfitting through bootstrapping and decision tree aggregation makes it effective in diverse environmental condition.

The most notable trend is the dramatic increase in the use of "Machine Learning" and "Deep Learning" methods from 2019 to 2024. The count for "Machine Learning" rose from 118 (2014–2019) to 1,325 (2019–2024), while "Deep Learning" appears with a count of 686 in the latter period, absent in the earlier timeframe. This surge underscores the rapid application of advanced machine learning algorithms and neural networks in recent rainfall forecasting research.

Deep learning models have gained considerable prominence, particularly "Long Short-Term Memory (LSTM)" and "Convolutional Neural Networks (CNN)."

As shown in Figure 2, "LSTM" has a count of 450 and "CNN" appears with 133 mentions in the 2019–2024 period, highlighting a strong research focus on model's adept at handling complex temporal sequences (LSTM) and spatial data (CNN). CNNs have become increasingly relevant due to their strength in identifying localized rainfall patterns from satellite and radar imagery, making them ideal for nowcasting and flash flood forecasting.

Furthermore, the rise of "Multilayer Perceptron (MLP)" from 28 (2014–2019) to 113 (2019–2024) illustrates the ongoing relevance of neural network architectures. MLPs continue to serve as accessible and flexible models for small-to-medium scale forecasting problems and are often used as baseline neural network architectures for comparison with more advanced models. These increases emphasize the field's shift towards deep learning techniques for capturing intricate patterns in rainfall data.

Traditional machine learning models, including "Support Vector Machine (SVM)," "Random Forest (RF)," and "Linear Regression," have maintained a consistent presence but exhibit varying levels of popularity. As observed in Figure 2, "SVM" counts increased from 49 to 129, and "Random Forest" saw a remarkable rise from 22 to 342, indicating their continued applicability in specific rainfall forecasting scenarios. SVM has remained popular for its effectiveness in high-dimensional, low-sample-size problems and its resilience against overfitting, especially when kernel functions are applied. Conversely, "Linear Regression" also experienced an uptick from 28 to 154, suggesting its utility, potentially as a benchmark model or in simpler forecasting

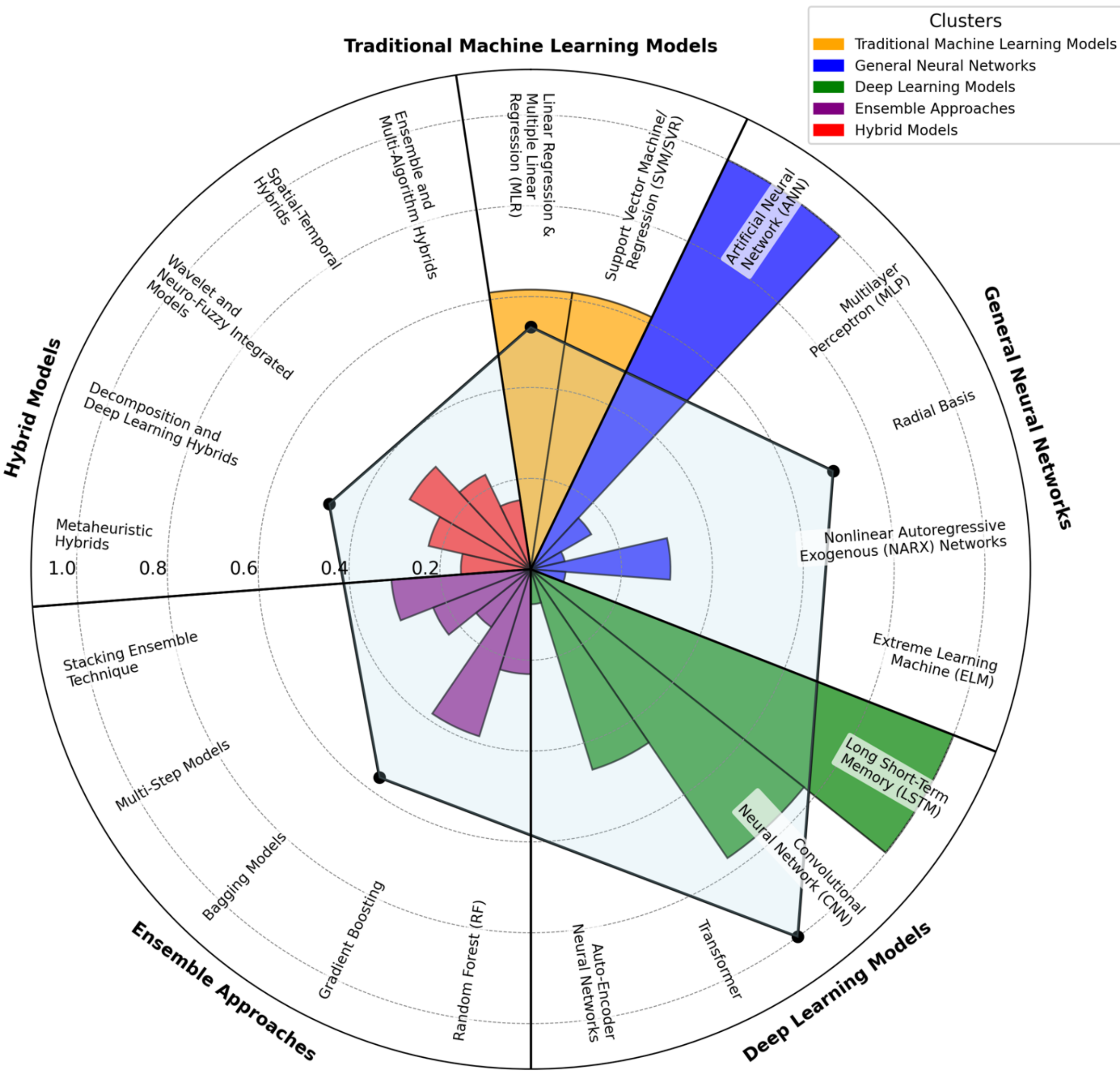


Figure 3 Clustered overview of Machine Learning Techniques in Rainfall Forecasting. The inner radial bars represent the relative frequency of different machine learning models across five clusters reviewed, while the outer line plot shows the aggregate model count within each cluster

applications. The absence of other traditional methods, such as "Support Vector Regression (SVR)" and "Least Square Support Vector Machine (LSSVM)," in the 2019–2024 period may indicate a research shift towards more advanced or ensemble-based approaches.

"Ensemble" methods have seen a substantial increase, with counts rising from 201 (2014–2019) to 674 (2019–2024). This trend reflects the increasing use of ensemble learning to enhance accuracy, reduce variance, and build resilience to overfitting by aggregating predictions from multiple models. The appearance of "Extreme Gradient Boosting (Xgboost)" exclusively in the 2019–2024 period (count of 93) further signifies the adoption of advanced ensemble techniques. XGBoost, in particular, has gained popularity for its high accuracy, regularization capabilities, and ability to handle missing data—traits valuable in complex meteorological datasets.

The radar chart in Figure 3 highlights this trend by illustrating Ensemble Approaches as one of the dominant clusters, underlining their effectiveness in improving forecasting reliability.

"Artificial Neural Network (ANN)" remains a notable term, increasing from 189 (2014–2019) to 328 (2019–2024), indicating sustained interest in general neural network approaches. However, other neural network variants like "Extreme Learning Machine (ELM)" and "Wavelet-based Artificial Neural Network (WANN) do not appear in the recent period, suggesting a consolidation towards more sophisticated or specialized neural network models, such as those in deep learning. This shift suggests researchers are focusing more on scalable, deep architectures capable of learning both spatial and temporal features simultaneously, rather than shallow or highly specific architectures.

The introduction of 'Precipitation Nowcasting' (count of 131) in the 2019–2024 period points to an emerging interest in real-time rainfall prediction methods. However, the decline in specific methods, such as 'Genetic Algorithm' and 'Radial Basis' (both absent in 2019–2024), indicates a research shift towards more data-driven models. In the literature, 'Radial Basis' has diverged into two distinct paths: its use in Radial Basis Function Networks (RBFNs) and as a Radial Basis Function Kernel in support vector machines. The decline of these methods likely reflects the increasing demand for models that scale well with data volume and support complex non-linear relationships, which are better addressed by DL or ensemble methods.

The data reveal a clear evolution in rainfall forecasting methodologies, with a significant surge in the adoption of deep learning and ensemble models, indicating their effectiveness in modelling the complex, non-linear relationships within rainfall data. The clustering into (1) Traditional Machine Learning Models, (2) General Neural Networks, (3) Deep Learning Models, (4) Ensemble Approaches, and (5) Hybrid Models (refer to Figure 1) provides a framework for understanding the diversity and progression of methodologies applied in rainfall forecasting research over the past decade.

While advanced models dominate current research trends, traditional machine learning methods continue to play a role, particularly for interpretability and benchmarking against newer, more complex models. General Neural Networks in this context refer to foundational neural network models like Artificial Neural Networks (ANN) and Multilayer Perceptron (MLP), which are relatively shallow architectures. In contrast, Deep Learning Models encompass more advanced architectures, such as Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks, which utilize deeper layers to learn complex hierarchical features from the data. This reflects an overall shift in the research community toward models that can capture spatiotemporal dependencies and leverage multi-source data, even as simpler models remain valuable for specific use cases.

The analysis illustrates the field's transition towards leveraging advanced, flexible, and integrated machine learning models to tackle the challenges of rainfall forecasting.

4.0 CLUSTER 1: TRADITIONAL MACHINE LEARNING MODELS

Traditional Machine Learning (ML) models have been widely employed in rainfall forecasting due to their simplicity and interpretability. This section reviews core models frequently applied in recent literature assessing their performance, strengths, limitations, and potential areas for improvement.

4.1 Linear Regression (LR) and Multiple Linear Regression (MLR)

Linear Regression (LR) and Multiple Linear Regression (MLR) are commonly applied for rainfall forecasting, especially due to their straightforward approach. These models often leverage meteorological variables to predict rainfall patterns across diverse regions. Many studies highlight strong correlations between rainfall and climate indices—parameters that capture large-scale atmospheric and oceanic conditions impacting weather systems. For instance, the Southern Oscillation Index (SOI) reflects atmospheric pressure differences between Tahiti and Darwin, Australia, acting as a key factor in monitoring El Niño-Southern Oscillation (ENSO) events [9]. Similarly, the Dipole Mode Index (DMI) measures temperature differentials in the Indian Ocean, influencing monsoon patterns and regional rainfall [10]. LR models are effective for detecting long-term seasonal and annual rainfall trends, providing valuable insights into shifts in precipitation patterns over time due to climate variability [9].

Incorporating climate indices like SOI and DMI into MLR models enhances forecast accuracy by capturing large-scale climatic drivers of localized weather, especially useful for seasonal and long-term forecasts [10], [11]. Although efficient, LR and MLR struggle to model the non-linear dynamics typical of complex climate systems, limiting their efficacy in intricate forecasting tasks) [11]–[15]. Interestingly, recent studies indicate LR may outperform complex models, like Decision Trees (DT) and XGBoost, for long-term trend forecasting. For instance, LR delivered accurate long-term predictions in a study for Thiruvananthapuram, Kerala, outperforming DT and XGBoost for predictions up to 2035, particularly with 50-year datasets [16]. This demonstrates the potential of LR for simpler, long-term analyses focused on broad trends, especially in regions with extensive historical data.

However, despite computational efficiency, MLR lacks the ability to capture non-linear relationships inherent in many climatic interactions, making it less suitable for forecasting extreme rainfall events or highly variable short-term patterns [11]–[15]. MLR's predictive accuracy can also suffer if essential variables are missing or data exhibits high variability, as with seasonal rainfall [15]. Thus, while MLR is a useful tool for interpretable, simpler models, it faces limitations in handling complex, non-linear phenomena.

4.2 Support Vector Regression (SVR)

Support Vector Regression (SVR), an extension of Support Vector Machines (SVM), is tailored for regression tasks by predicting continuous values. In rainfall forecasting, SVR has been applied for predicting values like monthly precipitation, Standardized Precipitation Index (SPI), and drought indices. Hybrid SVR models—such as SVR-RSM, SVR-ARIMA, fuzzy-SVR, boosted-SVR, and EEMD-SVR—are commonly used to enhance forecast accuracy by addressing non-linearities and improving computational efficiency [17]–[19].

Variants like Least Square Support Vector Machine (LSSVM) have been explored for rainfall downscaling and monthly precipitation forecasting, often as part of ensemble frameworks rather than standalone models [20], [21]. Comparative studies highlight that hybrid models, like ARIMA-NF (Neuro-fuzzy) and ARIMA-HW (Hammerstein-Weiner), can outperform LSSVM and ARIMA-LSSVM hybrids for daily rainfall prediction [22]. These models, particularly in drought forecasting using SPI on a monthly timescale, have shown SVR's potential over other machine learning models (e.g., ANN, RF, DT, and ANFIS) in some contexts [23], [24]. However, it's essential to note that such results may vary with different timescales or climate indices, suggesting that model suitability is context-dependent.

5.0 CLUSTER 2: GENERAL NEURAL NETWORKS

This section reviews general neural network models commonly applied in rainfall forecasting. These models range from foundational architectures like Artificial Neural Networks (ANNs) and Multilayer Perceptrons (MLPs) to specialized approaches such as Radial Basis Function (RBF) Networks and Nonlinear Autoregressive Exogenous (NARX) Networks, and even experimental designs like Weight Agnostic Neural Networks (WANN). Each offers unique strengths in modeling complex atmospheric variables, with varied performance, capabilities, and limitations.

5.1 Artificial Neural Network (ANN)

Artificial Neural Networks (ANNs) are among the earliest and most widely adopted neural network models, designed to mimic the structure of the human brain by using interconnected nodes (neurons) to process information. ANNs capture non-linear mappings between input and output data through hidden layers that apply non-linear transformations [25], [26]. In rainfall forecasting, ANNs have been extensively used to model complex meteorological relationships, incorporating variables like Sea Surface Temperature (SST), humidity, and wind speed to predict rainfall events [27], [28].

Compared to Multiple Linear Regression (MLR), ANNs capture non-linear data relationships more effectively, as MLR's linear assumptions restrict its ability to model the complex interactions typical of climate data [14]. However, ANNs require more computational resources and are prone to overfitting, especially with small datasets, while MLR remains simpler and easier to interpret. Similarly, in contrast to Support Vector Regression (SVR), ANNs provide greater flexibility in learning complex relationships through multiple hidden layers, while SVR's kernel functions are often favoured for smaller datasets due to their efficient handling of non-linear data with fewer hyperparameters [23], [24]. However, with large training datasets, ANNs can outperform SVR by learning complex feature interactions more effectively.

A notable ANN variation is reservoir computing, an efficient approach for time series forecasting. This architecture consists of three layers (input, reservoir, and output), training only the output layer, which simplifies computational complexity. It has been shown to handle non-smooth precipitation data, achieving improved forecasting accuracy with limited computational demands. A study that combined reservoir computing with pre-processing techniques like moving averages and logarithmic transformations demonstrated improved rainfall pattern predictions, highlighting its applicability in resource-constrained scenarios [29].

ANNs' adaptability makes them suitable for regions with noisy or incomplete data, incorporating diverse meteorological inputs effectively. However, they rely heavily on high-quality data and complex network architectures to avoid overfitting. Regularization techniques or early stopping can improve model generalization, especially when dataset size is limited. ANNs have been applied to predict monthly rainfall and indices such as the Standardized Precipitation Evapotranspiration Index (SPEI), Standard Index of

Annual Precipitation (SIAP), El Niño Southern Oscillation (ENSO), Indian Ocean Dipole (IOD), and Standardized Water Storage Index (SWSI) [30]–[34]. Studies often compare base ANN models to hybrid versions, which typically achieve better performance, as discussed further in Section 10.

One study trained an ANN model to predict rainfall with a 24-hour lead time by extracting pixel values from satellite infrared and water vapor images, enabling accurate short-term forecasts by learning atmospheric patterns from satellite data [35]. Similarly, combining ANN models with numerical weather prediction (NWP) models and satellite imagery has proven effective in short-term rainfall forecasting. For example, a quantitative precipitation forecast (QPF) model used infrared and visible satellite images with NWP data to produce one-hour rainfall forecasts, yielding satisfactory R^2 values for flood-prone areas [36].

In some contexts, however, traditional models may outperform ANNs. In a comparison of SANN and SARIMA for rainfall frequency forecasting, SARIMA showed lower errors in MSE and RMSE [37], suggesting that statistical models like SARIMA can be advantageous for time series data with strong seasonal components. Additionally, ANNs may require extensive datasets and computational resources, and without careful tuning, they risk overfitting. Consequently, the choice of model depends on dataset characteristics, the forecasting task, and available computational resources.

5.2 Multilayer Perceptron (MLP)

The Multilayer Perceptron (MLP) is a specific type of ANN featuring one or more hidden layers between input and output layers, classifying it as a feedforward neural network. Each hidden layer contains neurons with non-linear activation functions, such as ReLU, sigmoid, or tanh, allowing MLPs to capture complex relationships between input variables.

In rainfall forecasting, MLPs have been widely used to model non-linear relationships between meteorological parameters and rainfall. A study that tested 25 different MLP models with varied input combinations (e.g., temperature, wind speed, solar radiation) demonstrated the model's adaptability, allowing it to optimize forecasting accuracy based on available data [28]. A hybrid MLP model, MLP-WOA (Multilayer Perceptron-Whale Optimization Algorithm), provided improved accuracy over the base MLP for rainfall forecasting, though the benefits varied by metric and location, indicating that hybrid methods like MLP-WOA may be context-dependent [38].

5.3 Radial Basis Function (RBF) Networks

Radial Basis Function (RBF) Networks employ radial basis functions as activation functions in their hidden layers, making them effective for capturing localized data relationships. Each neuron in the hidden layer is activated based on the distance between the input vector and a predefined center, often using Gaussian activation functions, which activate neurons when inputs are near their centers. RBF Networks have been effectively used in rainfall forecasting, as demonstrated in a study where RBF outperformed ANN algorithms like the Gradient Descent Algorithm (GDA) and Scaled Conjugate Algorithm (SCG) in annual rainfall prediction [39].

5.4 Nonlinear Autoregressive Exogenous (NARX) Networks

The Nonlinear Autoregressive Exogenous (NARX) Network is a specialized neural network designed for time-series data, using both past values of output and external inputs (exogenous variables) for predictions. In NARX Networks, feedback connections make them a variant of recurrent neural networks (RNNs), capable of handling temporal dependencies effectively. NARX models capture temporal dynamics between variables like precipitation, evaporation, and temperature, making them powerful tools for predicting drought and the Standardized Precipitation Index (SPI) in various climates [40], [41].

NAR models, while similar to NARX, rely only on past target values (e.g., rainfall) without exogenous inputs. In a study on arid region rainfall forecasting, NAR outperformed ARIMA by effectively capturing simple climatic dynamics in rainfall prediction [42]. NARX's inclusion of external factors like temperature and humidity gives it an advantage in regions with more dynamic climates. However, training NARX networks can be computationally intensive, and they may overfit if the input data is noisy or incomplete. In contexts where physical data (e.g., soil moisture) is unavailable, NARX remains a viable alternative to physically based models like SM2RAIN [43].

5.5 Extreme Learning Machine (ELM)

The Extreme Learning Machine (ELM) is a single-layer feedforward neural network (SLFN) known for rapid learning. By assigning input weights and biases randomly and calculating output weights analytically, ELM eliminates the need for iterative optimization, reducing computational time significantly while maintaining high predictive performance. ELM has shown effectiveness in predicting drought indices like the Standardized Precipitation Index (SPI). Comparative studies found ELM consistently outperformed models like Random Forest (RF), MPMR, and M5 Tree, achieving the lowest root mean square error (RMSE) values across multiple timescales (1, 3, 6, and 12 months) [44]. The adaptability and efficiency of ELM make it suitable for long-term forecasting and resource-critical applications in environmental and climate research.

6.0 CLUSTER 3: DEEP LEARNING MODELS

Deep Learning (DL) has revolutionized rainfall forecasting by modelling complex and non-linear relationships in meteorological data, outperforming traditional and some advanced ML methods. As detailed in Section 5, Overview Analysis, DL terms were largely absent in articles from 2014 to 2019. However, the past five years (2019-2024) have seen a rapid rise in DL applications, making DL terms the second most common n-grams after machine learning. This growth underscores DL's expanding role in meteorology and climate forecasting, as DL models—particularly Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks—excel at capturing spatial and temporal dependencies crucial for predicting complex rainfall patterns associated with variables such as temperature, humidity, wind, and sea surface temperatures.

Recent DL-based advancements in nowcasting demonstrate promising improvements in predicting heavy rainfall events (HREs), where rapid and sporadic precipitation development complicates short-term forecasts. A notable approach that combined radar images with ground-based measurements achieved an impressive 162% improvement in accuracy over conventional numerical models for 1- to 6-hour HRE forecasts, proving DL's value for real-time forecasting [45]. These innovations suggest that DL-based nowcasting models could supplement operational numerical models in areas where precise HRE prediction is critical for disaster preparedness.

New DL nowcasting methods have also incorporated atmospheric factors like air divergence and water vapor, which influence rainfall formation. Integrating these elements enables DL models to better capture rainfall dynamics and reduce false alarm rates. Compared to radar-based methods, these enriched DL models capture moderate to severe rain events more accurately, strengthening early warning systems and forecasting reliability [46].

6.1 Convolutional Neural Networks (CNNs)

Primarily used for image and spatial pattern recognition, Convolutional Neural Networks (CNNs) have been adapted for rainfall forecasting due to their ability to capture spatial dependencies in meteorological data. CNNs process satellite images and radar data to identify cloud patterns, making them valuable for short-term rainfall predictions where spatial relationships are critical. CNN-based models have been operationally tested in flood-prone regions, such as in India, where district-level forecasts using U-Net CNNs aligned closely with ground-truth data from the Indian Meteorological Department (IMD). In another case, a CNN-TL (transfer learning) model was successfully applied to forecast heavy rainfall in South China, integrating local data with pretrained features. [47].

An advanced CNN-based architecture, the multi-scale feature fusion (MFF) model, uses convolutional kernels of varying sizes to capture essential precipitation features like shape, direction, and speed. MFF's multi-scale approach has proven effective in detecting intense rainfall, outperforming models like time series residual convolution (TSRC) and U-Net in short-term heavy precipitation forecasts, achieving high accuracy with reduced false alarms [48]. Despite their strengths, deploying CNNs in real-world systems poses challenges such as high computational costs, dependency on real-time satellite data streams, and difficulties in model interpretability. These factors limit their use in low-resource or time-critical operational environments.

Moreover, the Spatiotemporal Convolutional Sequence to Sequence Network (STConvS2S) model extends CNNs to capture both spatial and temporal dependencies, outperforming traditional RNN-based models in rainfall and air temperature forecasting for South America. CNNs have also outperformed models like ANN and ARIMA in forecasting monthly rainfall totals in hydrological basins, though a hybrid ANN-ARIMA model provided the highest accuracy for water resource management [49], [50].

Another noteworthy CNN variant, the 3D Convolutional Neural Network (3D-CNN), demonstrated superior performance in predicting daily precipitation, with a millisecond-scale inference time that enables real-time applications. Trained on 39 years of U.S. precipitation data, the 3D-CNN outperformed leading weather models for heavy precipitation events, making it suitable for daily forecasts up to 5 days ahead [51]. The Deep Learning Weather Prediction (DLWP) model, another CNN variant, effectively generated six-week global forecasts on atmospheric variables in three minutes, demonstrating its applicability in subseasonal-to-seasonal (S2S) forecasts comparable to ECMWF [52].

U-Nets, a CNN extension optimized for high-resolution spatial predictions, excel in complex terrains, particularly in district-level rainfall forecasting for flash-flood-prone areas. U-Nets, especially when paired with spatial attention, show superior accuracy in regions like India, aligning predictions with actual observational data from agencies like the India Meteorological Department (IMD), a feat challenging for conventional models like WRF [53]–[55]. Further enhancements like frequency-based loss weighting improve U-Nets' forecasting for heavy rainfall, highlighting their utility in extreme weather scenarios [56].

6.2 Long Short-Term Memory (LSTM)

Recurrent Neural Networks (RNNs), particularly Long Short-Term Memory (LSTM) networks, are widely adopted in rainfall forecasting for their ability to capture sequential and temporal dependencies. LSTMs outperform models such as MLP, KNN, SVM, and RF in forecasting both long- and short-term rainfall and weather indices like SPI, as they capture extended patterns in meteorological data [57]–[64]. LSTM-based rainfall prediction models have been explored for monsoon forecasting in countries like India, Bangladesh, and Ghana, where long-term dependencies in rainfall sequences are essential for planning. Some national weather services have begun integrating LSTM models as supplementary tools for sub-seasonal forecasting.

For example, LSTM models have accurately forecasted daily, monthly, and seasonal rainfall by modeling the temporal relationships among factors like SST and sea level pressure. One model incorporating SST and Nino 3.4 index data showed high correlation with real observations for up to four months, underscoring LSTM's value in water resource management [65]. LSTM has also proven effective for rainfall predictions in regions with monsoon variability, such as northeastern India [65]. In Ghana, multivariate LSTM models successfully captured monthly rainfall patterns across various regions, outperforming SVR and RF [61]. However, the operational deployment of LSTM models remains limited due to long training times, sensitivity to missing data, and the requirement for large, clean time series datasets. These models are also often treated as "black boxes," making it difficult for policymakers or disaster response teams to interpret predictions without supplementary explanations.

Advanced LSTM variations, such as Intensified LSTM with optimized learning rates and loss functions, outperform models like Holt-Winters and ARIMA with lower RMSE values. Integrating LSTM with Adaptive Moment Optimization (AMO) has yielded high accuracy (~95%) in big data contexts, while Bidirectional-LSTM combined with Instantaneous Frequency (IF) excels in multi-step daily rainfall forecasts with R^2 values reaching 0.9983 [66]–[69].

6.3 Transformers

Transformers present a powerful alternative to sequential models, utilizing self-attention mechanisms to process temporal data in parallel, improving efficiency and performance for large meteorological datasets. A transformer model trained on 41 years of rainfall data in India demonstrated superior accuracy over LSTM and GRU, effectively capturing spatial-temporal patterns for large-scale forecasts [70].

To address longer forecasting horizons, the Short-Term Precipitation Forecast Network (STPF-Net) incorporates a multi-tier transformer structure that manages longer lead times (6–12 hours) by optimizing spatial and temporal resolution, with improved accuracy for 6-hour precipitation forecasts in southeastern China [71]. Additionally, transformer models with multi-head attention modules improve short-term nowcasting accuracy, and physics-informed transformers like LPT-QPN leverage meteorological insights to excel in high-intensity rainfall events [72] [73].

Further advancements in transformer architectures include the AdaNAS, an automated neural architecture search method that customizes model design for rainfall forecasting, achieving an 80% reduction in MAE and RMSE. Additionally, transformer-based generative models with radar composite data have outperformed traditional methods for short-term convective rainfall nowcasting, underscoring their value in dynamic, region-specific applications [74] [75].

6.4 Auto-Encoder Neural Networks

For regions with flood-prone rain belts, particularly in years without strong external forcing signals, short-term climate predictability remains challenging. A novel climate index using Auto-Encoder (AE) Neural Networks demonstrated superior performance in forecasting significant precipitation events under varying El Niño conditions. This approach enhanced prediction accuracy during the summer precipitation of 2020, highlighting AE networks' potential in creating climate indices that refine flood forecasting and water resource planning [76].

7.0 CLUSTER 4: ENSEMBLE APPROACHES

Ensemble methods leverage multiple models to enhance accuracy and robustness in precipitation and drought forecasting. This section outlines various ensemble techniques and their effectiveness.

7.1 Random Forest

Random Forest (RF) models have proven effective for predicting weather indices like the Standardized Precipitation Index (SPI) by aggregating predictions from multiple decision trees, which reduces variance and improves predictive performance [24]. Recent studies have applied RF to Subseasonal-to-Seasonal (S2S) precipitation forecasting, particularly for extreme events in the contiguous United States (CONUS). Enhanced by additional forecast variables (e.g., surface air temperature and geopotential heights), RF showed improved forecast skill for lead times beyond week 2, and further tuning of tree depth enhanced forecast accuracy across CONUS [77].

A recent probabilistic RF-based system used NOAA's GEFS/R reforecast data to predict locally extreme precipitation over CONUS, focusing on 24-hour accumulations across two severity levels. Trained with 11 years of reforecast data, the RF model incorporated predictors like quantitative precipitation forecasts, winds, moisture, and instability. The RF forecasts outperformed both raw GEFS/R QPFs and ECMWF ensemble forecasts, demonstrating superior performance for operational sub-seasonal to seasonal (S2S) rainfall prediction in the United States [78].

Evaluation metrics such as the Brier Skill Score (BSS), Ensemble Critical Success Index (ECSI), and Area Under the Receiver Operating Characteristics Curve (AUROC) confirmed that supplementing RF models with additional forecast variables enhances S2S extreme precipitation forecasting. These improvements highlight RF's applicability in flood forecasting and water resource management.

7.2 Gradient Boosting

Gradient boosting models, including Gradient Boosting Decision Tree (GBDT), LightGBM, CatBoost, and XGBoost, consistently outperform traditional models in precipitation forecasting. In Eurasia, CatBoost has shown high precision for urban rainfall predictions with minimal Mean Absolute Error (MAE) and Root Mean Square Error (RMSE), while XGBoost effectively handles complex data patterns for short-term and seasonal forecasts [79]–[82].

AdaBoost, a variant, has also demonstrated utility in forecasting by improving accuracy and lowering error rates compared to models like SVM. For instance, in Indian hydrological data (1901-2015), AdaBoost showed superior performance, emphasizing its potential for rainfall prediction across diverse regions [83]. It's crucial to distinguish AdaBoost, a boosting method combining multiple learners, from AdaNAS, which automates neural architecture design for meteorological tasks.

7.3 Multi-Step Model Approaches

Multi-step models that leverage sequential data have been applied to rainfall and seasonal forecasting by capturing temporal dependencies. For instance, a multi-step approach integrating ARIMA, LSTM, and XGBoost in rainfall forecasting showed that while LSTM captured temporal dependencies well, XGBoost's final stage refinement yielded optimal accuracy [84].

In Indian Summer Monsoon Rainfall (ISMR) forecasting, multi-step models like the regularized online sequential RVFL (ROS-RVFL) excelled over single-layer neural networks by training on optimal historical data intervals. The ROS-RVFL model demonstrated superior accuracy when trained on 8–9 years of data, underscoring its efficacy for monsoon forecasting [85].

Further, the Synthetic-data Task-segmented Generative Model (STGM) for rainfall nowcasting segments high-intensity precipitation events over a 6-hour horizon. This AI-driven approach effectively tracks storm cell evolution, enhancing prediction quality for disaster management and public safety [86].

7.4 Bagging Ensemble Learning Models

Bagging ensembles combining models like Random Trees (RT), Locally Weighted Learning (LWL), and k-Nearest Neighbor (kNN) have shown success in precipitation forecasting. For example, a Bagging LWL-RT model outperformed alternatives in specific locations, while Bagging LWL-kNN was more effective elsewhere, revealing region-specific dependencies [87]. Another study validated Bagging Tree and M5Pruned (M5P) models for SPI predictions across three stations in India, showing reliable mid-term drought forecasts for drought management [88].

7.5 Stacking Ensemble Technique

Stacking, a technique that combines multiple models, has shown further enhancements in prediction accuracy. In one study, a stacked ensemble of XGBoost, RF, and LightGBM effectively forecasted drought indices like SPEI, achieving an R^2 of 0.845 [89]. Another multi-view stacking approach improved monthly precipitation predictions by combining Decision Tree, KNN, AdaBoost, XGBoost, and LSTM, with XGBoost as the second-level learner [90].

In another real-world case study, a stacked ensemble model in Romania significantly improved Quantitative Precipitation Estimation (QPE) by 33% compared to radar-only methods. The model combined radar data with machine learning techniques, proving its value in enhancing real-time flood prediction and early warning capabilities [91].

Together, these findings demonstrate stacking's effectiveness in optimizing weather and climate forecasts, especially when utilizing advanced radar data and machine learning techniques.

8.0 CLUSTER 5: HYBRID MODELS

Hybrid models have advanced rainfall forecasting by combining various techniques, capturing complex meteorological patterns more effectively than single-model approaches. This section presents hybrid models grouped into broader methodological clusters, illustrating their unique strengths and applications.

8.1 Metaheuristic and Optimization-Based Hybrids

Metaheuristic optimization techniques, such as the artificial bee colony (ABC) algorithm, have successfully enhanced traditional models like Support Vector Regression (SVR), improving accuracy in hydrological time-series forecasting. For instance, the SVR-ABC model outperformed Random Forest (RF) and other hybrid models, highlighting the benefits of metaheuristic optimization [92]. Other studies have integrated algorithms like K-Nearest Neighbor (KNN), XGBoost (XGB), and Decision Tree (DCT), demonstrating that combining machine learning methods with optimization techniques can achieve high accuracy, as seen in rainfall forecasting at Sydney Airport, Australia [93].

8.2 Decomposition and Deep Learning Hybrids

Integrating decomposition techniques with deep learning enables models to capture intricate patterns in rainfall data. Models like CEEMDAN-VMD-BiLSTM and ESMD-EWT-SVD-LSTM leverage multi-level decompositions to enhance predictive performance, particularly for monthly rainfall. These models combine decomposition methods (e.g., CEEMDAN, VMD, EWT) with deep learning architectures like BiLSTM and LSTM, resulting in models that can effectively capture nonlinear dependencies and trends in complex datasets [94], [95].

8.3 Wavelet and Neuro-Fuzzy Integrated Models

Wavelet analysis and neuro-fuzzy systems have proven effective in capturing variability in rainfall data. Wavelet-integrated models, such as Wavelet Packet Transform (WPT)-ANN and Adaptive Neuro-Fuzzy Inference System (ANFIS), have shown significant improvements in forecasting accuracy. Additionally, models like the Wavelet-based ANN (WANN) and Wavelet Neural Network (WNN) are particularly adept at predicting extreme precipitation and future climate scenarios, using meteorological inputs like temperature and humidity to improve predictions [96]–[99].

8.4 Spatial-Temporal and Attention-Based Hybrids

Models that incorporate spatial-temporal data and attention mechanisms have enhanced interpretability and forecasting precision. For example, the interpretable spatial-temporal attention convolution network (IDSTA-TCN) utilizes Bayesian-optimized decomposition alongside spatial-temporal attention, dynamically incorporating data from surrounding meteorological stations. This approach enables more reliable and interpretable predictions, especially for regional hydrological applications [100].

8.5 Ensemble and Multi-Algorithm Hybrids

Combining multiple machine learning algorithms into ensemble hybrids offers robust solutions for rainfall prediction. Models like the deep residual shrinkage network (DRSN)-TCN-RF and U-Net with partial differential equations (PDE) have shown high precision in short-term and daily forecasts. These hybrids leverage the strengths of different algorithms—such as convolutional, recurrent, and residual networks—to improve overall forecast reliability, particularly in operational nowcasting and multi-hour prediction windows [101] [102].

8.6 Extreme Event and Spatiotemporal Autocorrelation Hybrids

To address the challenges of forecasting extreme precipitation, hybrid models like the MLP-CNN and deformable convolutional LSTM (DConvLSTM-SAC) have shown promising results. These models use atmospheric features and spatial autocorrelation techniques (e.g., local Moran index) to enhance accuracy for extreme event predictions, particularly in early warning systems. Such methods are essential for accurately predicting rare, high-impact weather events that require spatial awareness for effective response [103] [104].

8.7 Advanced Decomposition with Gated and Attention Mechanisms

Integrating advanced decomposition techniques with gated networks and attention mechanisms has proven effective in capturing stochastic rainfall patterns. A recent hybrid model combining Variational Mode Decomposition (VMD) with a gated convolutional network, optimized by Gelu and attention functions, demonstrated high predictive accuracy across real-world datasets, underscoring the power of combining decomposition with deep learning for daily rainfall forecasting [105].

9.0 DISCUSSION

Hybrid models have advanced rainfall forecasting by combining various techniques, capturing complex meteorological patterns more effectively than single-model approaches. This section presents hybrid models grouped into broader methodological clusters, illustrating their unique strengths and applications.

9.1 Evolution of Model Complexity

The shift from simpler models, such as Linear Regression (LR) and Support Vector Regression (SVR), to DL models like Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks, underscores a trend towards increasingly complex architectures. These models are known for their capability to capture nuanced spatial-temporal patterns in meteorological data, making them valuable for real-time applications such as nowcasting and short-term heavy precipitation forecasting [25], [26] , [47]. However, the complexity of DL models brings forth contradictions in their efficacy when contrasted with traditional models.

Contradiction: Although DL models like CNNs and LSTMs are generally considered superior in accuracy, some studies indicate that traditional models like LR can outperform advanced architectures in specific contexts, particularly for long-term trend forecasting. For instance, a study on rainfall trends in Thiruvananthapuram, India, demonstrated that LR provided more accurate long-term projections than Decision Trees (DT) and XGBoost, suggesting that simpler models may still be advantageous when the primary focus is on broad trend forecasting rather than capturing complex, short-term interactions [16].

However, one of the most common limitations of deep learning models in this domain is their tendency to overfit when trained on limited or noisy meteorological datasets. This is due to the high number of trainable parameters and their sensitivity to fluctuations in time-series rainfall data, particularly when spatial inputs (e.g., satellite images) are sparse or inconsistent. Overfitting reduces model generalization and reliability in operational forecasting. To address this, techniques such as dropout regularization, early stopping, and cross-validation are widely used. In addition, data augmentation strategies and ensemble averaging can improve robustness, though they come with increased computational demands.

Table 1 Comparison of Machine Learning Models for Rainfall Forecasting

Topic	Key Insights	Supporting Studies	Context	Advantages	Recommendations
Linear Regression vs. Advanced Models	Advanced models (e.g., XGBoost) offer better accuracy but LR excels in long-term stable forecasts.	LR outperformed DT and XGBoost in long-term forecasting in Thiruvananthapuram, India ([16]).	Stable climates with extensive historical data.	LR: Simplicity, interpretability, low computational needs.	Test LR vs. advanced models across varied climates to clarify effectiveness.
Traditional vs. Deep Learning in Noisy Data	Traditional models (e.g., SVR) outperform DL in noisy/small datasets due to robustness.	SVR had lower error rates than ANN in noise-heavy datasets ([23], [37]).	Noisy datasets or limited pre-processing capacity.	SVR: Robust in unstable data; avoids overfitting in small datasets.	Combine DL's pattern recognition with SVR's noise resilience in hybrids.
Variability in Hybrid Models	Hybrid model choice depends on data/goals; ARIMA-NF and ARIMA-HW often outperform LSTM hybrids for simpler tasks.	ARIMA-NF and ARIMA-HW excel in daily forecasts ([22], [38]).	Data complexity, periodicity, and forecast horizon matter.	ARIMA-NF/HW: Adaptable and accurate for stable daily forecasts.	Develop frameworks to align hybrid models with data and goals.
Interpretability Challenges in DL	DL remains a "black box"; simpler models (e.g., DT, LR) preferred for transparent decision-making.	DL interpretability remains limited even with attention mechanisms ([25], [106]).	High-stakes settings requiring clear reasoning.	DT/LR: Transparent decision pathways for regulated contexts.	Develop interpretability-enhanced DL variants for critical applications.
Data and Computational Demand	DL models (e.g., CNN, LSTM) require substantial data/resources, favoring RF in resource-limited regions.	RF more viable in data-scarce regions ([99], [78]).	Low-resource areas with limited data availability.	RF: High accuracy with low data complexity.	Develop data-efficient DL models or use transfer learning for accessibility.

This finding highlight that while DL models excel at capturing transient and high-resolution data patterns, traditional models can sometimes provide better interpretability and generalization over extensive datasets, especially where long-term trends outweigh short-term variability. As a result, these contradictory findings suggest that model choice should be driven by forecast objectives and data characteristics, rather than by model complexity alone.

9.2 Emergence of Hybrid and Ensemble Models

The adoption of hybrid and ensemble approaches reflects an increasing awareness of the limitations of single-model applications and the value of combining methods to enhance robustness and accuracy. Models like CEEMDAN-VMD-BiLSTM and DRSN-TCN-RF exemplify the benefits of incorporating decomposition techniques, spatial-temporal data, and metaheuristic optimization to improve predictions under noisy or irregular data conditions [94] [95] [101] [102]. This trend signifies a departure from standalone models toward adaptive frameworks that can better address the inherent complexities of rainfall patterns.

Contradiction: Although hybrid models are generally assumed to provide superior performance, there is no consensus on the optimal hybrid configuration. Studies reveal that models such as ARIMA-NF (Neuro-fuzzy) and ARIMA-HW (Hammerstein-Weiner) hybrids can sometimes outperform LSTM-based hybrids, particularly in applications requiring daily rainfall forecasting. For instance, while LSTM-based hybrids are effective in capturing temporal dependencies, simpler statistical models like ARIMA-NF have shown superior performance in certain daily predictions, challenging the assumption that DL-based hybrids are universally advantageous [22], [38], [106].

These conflicting results suggest that while hybrid models have a proven track record of accuracy, no single configuration universally applies across all rainfall forecasting contexts. The variability in hybrid model efficacy implies that model selection must be carefully tailored to specific data characteristics, forecasting requirements, and model strengths, with a preference for simpler combinations in cases where data may lack the complexity required to benefit from DL layers.

While hybrid models show strong forecasting potential, they can introduce high computational overhead and reduced transparency due to their complexity. Additionally, ensemble techniques may suffer from redundancy or marginal performance gain when too many models are combined. To address these issues, researchers can consider using lightweight hybrid architectures, pruning of redundant learners, or selective stacking based on validation performance. Frameworks that balance predictive power with model interpretability—such as combining decision trees with LSTM or CNN backbones—also offer a promising compromise.

9.3 Performance of Traditional Models in Noise-Heavy Datasets

The emergence of DL models as dominant approaches in rainfall forecasting is largely due to their superior ability to capture non-linear and dynamic relationships among meteorological variables. However, not all data environments are conducive to the effective application of DL techniques. In contexts with limited or noise-heavy datasets, traditional models are sometimes preferred over DL due to their robustness against overfitting and reduced sensitivity to data quality.

Contradiction: Although DL models like CNNs and LSTMs generally achieve higher accuracy, they may underperform when data quality is poor or datasets are limited. Comparative studies suggest that traditional models, such as SARIMA and Support Vector Regression (SVR), yield lower error rates in noise-heavy datasets, where the high sensitivity of DL models to data irregularities can reduce their accuracy advantage [23], [24], [37].

This evidence underscores the limitations of DL models in unstable data environments and highlights the practicality of traditional models for less-controlled datasets. For regions with limited data quality or availability, traditional approaches may still provide a viable alternative, reinforcing the need for a flexible approach to model selection based on data context. This suggests the need for careful preprocessing of rainfall datasets before using DL models in such contexts. Techniques like denoising autoencoders, signal decomposition, or synthetic data augmentation may help improve model resilience without sacrificing performance.

9.4 Challenges with Interpretability and Transparency

DL models offer substantial accuracy improvements; however, they pose interpretability challenges that can hinder their adoption in operational forecasting, especially in contexts requiring clear reasoning behind predictions, such as flood management and emergency response. While attention mechanisms have been introduced to improve interpretability, research suggests that DL models may still function as "black boxes" compared to traditional ML approaches, which offer more transparency.

Contradiction: Despite advancements in DL interpretability through mechanisms like attention-based models (e.g., IDSTA-TCN), traditional models such as decision trees or linear models are often considered more transparent and interpretable. These models provide traceable decision pathways that make them preferable for applications requiring clear reasoning behind predictions [25], [26], [100].

This contradiction highlights a critical trade-off: while DL models provide enhanced accuracy, they may lack the operational transparency that traditional models afford. For forecasting applications where interpretability is essential, simpler, more transparent models may still be preferable, emphasizing the need to balance accuracy with transparency in model development. Recent efforts to improve deep model interpretability include applying SHAP (SHapley Additive Explanations) and LIME (Local Interpretable Model-agnostic Explanations), which help quantify feature importance in model outputs. Integrating these techniques into forecasting workflows could support transparent, actionable insights in operational settings like disaster preparedness and water resource planning [107].

9.5 Resource Limitations and Computational Constraints

The implementation of advanced models, particularly DL and hybrid approaches, often requires significant data and computational resources. In regions with limited access to high-quality data or infrastructure, the practical utility of complex models can be constrained, presenting a further contradiction to the assumption that advanced models are always preferable.

Contradiction: While models like CNN, LSTM, and various hybrid techniques offer high predictive accuracy, studies indicate that simpler models, such as Random Forest (RF) or LR, remain more feasible for regions with limited computational resources. The higher resource demands of DL models often make traditional ML models a more practical option in data-scarce regions [93], [78].

This finding suggests that while advanced models are theoretically optimal, their real-world application may be restricted in regions with limited infrastructure. Consequently, ensuring equitable access to high-quality forecasting tools may require an emphasis on resource-efficient models or innovative approaches like transfer learning, which enables training on larger datasets and subsequent application in resource-constrained environments. Additional solutions include the use of model compression techniques such as knowledge distillation, quantization, or sparse model training, which can significantly reduce the memory and computational footprint of deep models. Open-source pretrained models adapted through transfer learning also offer a pathway to scalable forecasting in data-poor regions [108].

9.6 Future Directions

The contradictions highlighted above underscore the importance of a nuanced approach to model selection in rainfall forecasting. While advanced models offer significant potential for accuracy and adaptability, traditional and simpler hybrid models retain relevance, particularly in data-limited or operationally sensitive contexts. Future research should focus on addressing data efficiency, interpretability, and computational accessibility to ensure that advancements in rainfall forecasting models are both scientifically robust and broadly applicable.

To address these ongoing challenges, promising directions include the development of data-efficient models that leverage transfer learning to expand advanced model utility across diverse regions, as well as efforts to incorporate remote sensing and IoT-based atmospheric sensors to enhance input data quality and availability. Additionally, future research should continue to prioritize balanced evaluation metrics, such as RMSE, MAE, and AUROC, along with interpretability metrics that support both technical performance and operational transparency [53]–[55], [96], [97], [105].

These findings, summarized in Table 1, underscore how specific model configurations may support or contradict each other, emphasizing the need for careful consideration of model complexity, data quality, and computational feasibility in various forecasting contexts. Table 1 provides a comparative summary of model advantages, limitations, and situations where simpler or more complex models excel, aligning with the findings discussed. Ultimately, building rainfall forecasting models that are not only accurate but also explainable, efficient, and scalable will be essential for widespread adoption in both research and policy contexts.

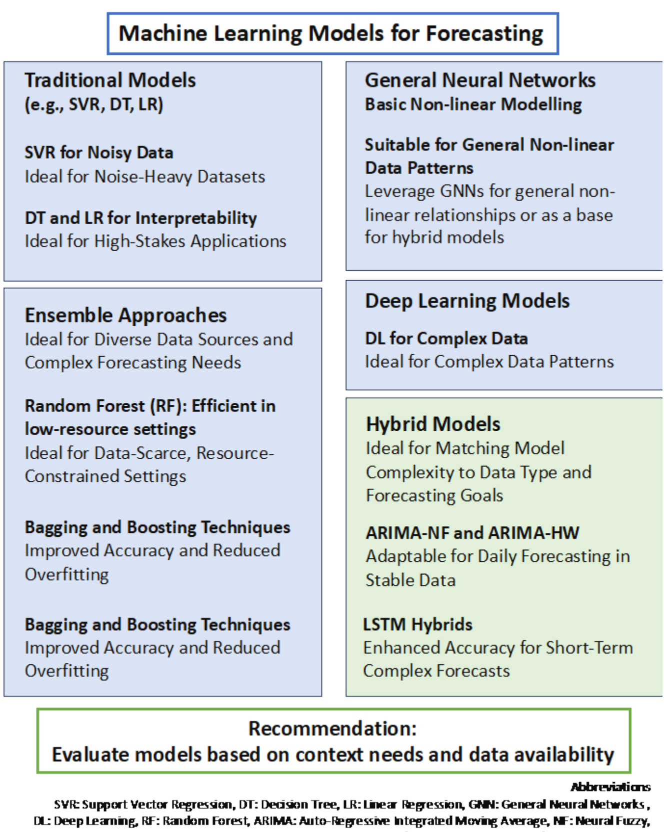


Figure 4 Summary of Machine Learning Models for Rainfall Forecasting

10.0 CONCLUSION

This review has outlined the evolving landscape of machine learning-based rainfall forecasting, from traditional ML models to advanced deep learning and hybrid approaches. Traditional models, such as Linear Regression (LR) and Support Vector Regression (SVR), have offered foundational insights but often fall short in capturing the nonlinear complexities and spatial-temporal dependencies of rainfall patterns. As rainfall forecasting demands increased precision and adaptability, researchers have shifted toward more sophisticated approaches that better address these challenges.

Deep Learning (DL) models, especially Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks, have shown marked improvements in predictive accuracy. These models excel in high-resolution forecasting and nowcasting applications, where their ability to model complex atmospheric interactions provides significant advantages. However, the computational demands and data requirements of DL models highlight the importance of developing efficient methods and exploring data augmentation techniques to make these models more accessible to a broader range of users.

Hybrid models, combining various ML and DL techniques, have emerged as particularly promising for capturing the multifaceted nature of rainfall forecasting. By leveraging decomposition methods, spatial-temporal data integration, and optimization algorithms, hybrid approaches like CEEMDAN-VMD-BiLSTM and DRSN-TCN-RF have achieved significant accuracy gains. These models underscore the potential of combining algorithms to overcome individual limitations, and they hold particular promise for complex forecasting tasks in regions with diverse climatic conditions.

Figure 4 visually summarizes the landscape of machine learning models for forecasting, categorizing them into Traditional Models, General Neural Networks, Ensemble Approaches, Deep Learning Models, and Hybrid Models. The figure highlights their respective strengths, applications, and suitability for various forecasting needs. The recommendation at the bottom underscores the importance of selecting models based on context, data availability, and specific forecasting requirements.

Despite these advances, several challenges remain. Deep learning and hybrid models often require large, high-quality datasets and significant computational resources, making them less accessible in low-resource settings. Furthermore, the limited interpretability of complex models continues to hinder their adoption in decision-critical applications such as flood forecasting and early warning systems.

Future research should focus on several key directions. First, the development of data-efficient learning techniques, such as transfer learning and few-shot learning, can help adapt pre-trained models to local rainfall conditions with minimal data. Second, efforts to improve model transparency—through explainable AI methods like SHAP, attention visualization, or surrogate modeling—are critical for trust and adoption by policymakers. Third, research should explore model compression methods such as pruning and quantization to reduce deployment barriers in regions with limited infrastructure. Fourth, integrating new data sources, such as IoT-based weather sensors, drone-based monitoring, and high-resolution satellite imagery, can improve real-time forecasting resolution. Finally, future studies should emphasize benchmarking ML models under unified frameworks using standard datasets, metrics (e.g., RMSE, MAE, AUROC), and interpretability scores to ensure fair and reproducible evaluations.

By addressing these challenges, the rainfall forecasting community can move toward models that are not only accurate and scalable but also transparent, efficient, and deployable in operational contexts. These advances will be critical to support disaster preparedness, agricultural planning, and climate resilience initiatives globally.

Acknowledgement

Authors would also like to thank and acknowledge the Innovative Electromobility Research Laboratory (ITEM) and Faculty of Electrical Engineering Universiti Teknologi MARA Shah Alam for their support.

Conflicts of Interest

The authors declare that there is no conflict of interest regarding the publication of this paper.

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