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Review

Potential of Artificial Intelligence-Based Techniques for Rainfall Forecasting in Thailand: A Comprehensive Review

Muhammad Waqas [1,2], Usa Wannasingha Humphries [3,*], Angkool Wangwongchai [3], Porntip Dechpichai [3] and Shakeel Ahmad [4,5]

1 The Joint Graduate School of Energy and Environment (JGSEE), King Mongkut's University of Technology Thonburi (KMUTT), Bangkok 10140, Thailand; muhammad.waqa@kmutt.ac.th
2 Center of Excellence on Energy Technology and Environment (CEE), Ministry of Higher Education, Science, Research and Innovation, Bangkok 10400, Thailand
3 Department of Mathematics, Faculty of Science, King Mongkut's University of Technology Thonburi (KMUTT), Bangkok 10140, Thailand; angkool.wan@kmutt.ac.th (A.W.); porntip.dec@kmutt.ac.th (P.D.)
4 Faculty of Environmental Science and Engineering, Kunming University of Science and Technology, Kunming 650500, China; shakeel@nankai.edu.cn
5 College of Environmental Science and Engineering, Nankai University, Tianjin 300350, China
* Correspondence: usa.wan@kmutt.ac.th

Abstract: Rainfall forecasting is one of the most challenging factors of weather forecasting all over the planet. Due to climate change, Thailand has experienced extreme weather events, including prolonged lacks of and heavy rainfall. Accurate rainfall forecasting is crucial for Thailand's agricultural sector. Agriculture depends on rainfall water, which is important for water resources, adversity management, and overall socio-economic development. Artificial intelligence techniques (AITs) have shown remarkable precision in rainfall forecasting in the past two decades. AITs may accurately forecast rainfall by identifying hidden patterns from past weather data features. This research investigates and reviews the most recent AITs focused on advanced machine learning (ML), artificial neural networks (ANNs), and deep learning (DL) utilized for rainfall forecasting. For this investigation, academic articles from credible online search libraries published between 2000 and 2022 are analyzed. The authors focus on Thailand and the worldwide applications of AITs for rainfall forecasting and determine the best methods for Thailand. This will assist academics in analyzing the most recent work on rainfall forecasting, with a particular emphasis on AITs, but it will also serve as a benchmark for future comparisons. The investigation concludes that hybrid models combining ANNs with wavelet transformation and bootstrapping can improve the current accuracy of rainfall forecasting in Thailand.

Keywords: artificial intelligence; machine learning; deep learning; neural networks; rainfall; forecasting

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1. Introduction

Rainfall forecasting is one of the most crucial functions of meteorological departments for all countries. Forecasting rainfall helps prevent flooding, thus preventing loss of lives and property. Moreover, it facilitates the management of water resources. Information on previous rainfall assists farmers in managing their crops more effectively, contributing to economic growth [1]. Meteorological experts have difficulty predicting rainfall due to its erratic timing and quantity. The task is extremely complicated because it requires many experts, and all communications are made without certainty [1]. Common parts of these problems are analyzing the past and applying future forecasting. The attributes required to forecast rainfall are complicated and nuanced, even on a short-term scale. The physical processes of rainfall typically consist of a set of sub-processes. Sometimes, a single global model cannot predict rainfall accurately. Precise rainfall forecasting is required to efficiently

estimate a country's water budget and plan, strategize, and maintain water storage choices under harsh weather circumstances. Despite tremendous breakthroughs in technology, practical and exact forecasting has remained a significant source of concern, demonstrating the magnitude of the problem. Several empirical and dynamical or mixed methods have been employed to generate decent rainfall prediction with improved accuracy [2]. Physical models based on equations that anticipate rainfall, such as Multi-variable Polynomial Regression, are used to make predictions in dynamical approaches [3].

Additionally, meteorologists have developed mathematical frameworks for estimating changes in temperature and pressure. The empirical techniques rely on historical data and its relationship to numerous regional climate variables [4]. Nevertheless, it has been demonstrated that such artificial intelligence techniques (AITs) have remarkable precision in rainfall forecasting [5,6]. Researchers are working on the accuracy of improving precipitation forecasts by enhancing and standardizing the data collection methods. According to recent studies, researchers prefer merged rainfall methods for forecasting when high precision is required [7]. Analyzing the time series dataset is an essential component of contemporary research in weather forecasting. Time series data are collected yearly, quarterly, monthly, weekly, daily, and hourly among the elements of meteorological data like humidity, temperature, wind speed, and air pressure [8]. AITs can extract patterns from the characteristics of previous weather records and utilize these trends to forecast upcoming weather conditions [9]. Numerous attempts have been made to determine the optimal method for rainfall forecasting, such as combining physical, oceanic, and meteorological or satellite observations with a forecasting model or employing multiple technologies like the artificial neural network (ANN) as a forecasting approach [10–12]. French et al. (1992) developed a feed-forward form of ANN for rainfall forecasting for the first time [13]. Because of their tremendous capacity to represent non-linear systems, ANNs have been utilized well in recent years for hydrological forecasting, particularly rainfall forecasting [10,14–16]. Thailand is a tropical country, and its agriculture and economy are highly dependent on rainfall. Thus, excessive or insufficient rainfall can devastate the national economy and the people's way of life. Therefore, a more profound comprehension of rainfall's spatial and temporal distributions is crucial for any country's economy [17]. About 13,100 acres of farmland are distanced from irrigated areas in Thailand, and rainfall plays a crucial role in the agricultural sector. This implies that 80% of the nation's farming relies on rainfall [18]. Therefore, identifying an accurate method for rainfall forecasting in Thailand is crucial. As previously mentioned, AITs have the potential to forecast rainfall accurately. A comprehensive literature review is required to study and identify the most appropriate AITs for Thailand. A high-quality literature review accomplishes its objective by providing precise information on the targeted study topic within the allotted time. A thorough research strategy with detailed instructions is vital for an effective literature review [19]. Therefore, a detailed methodology was developed to conduct this review, which is outlined in the subsequent section.

2. Materials and Methods

For the literature review in this study, all available developments in rainfall forecasting methods were first studied, and then we focused on the ATIs. Global applications of ML, ANN, and DL in rainfall forecasting were studied in the first half section of the review, highlighting the strengths and weaknesses of these techniques. The second section focused on Thailand to analyze the progress of AITs, and in this part, the study focused more on some DL techniques. Figure 1 provides an overall methodology of this review, comprising a systematic framework to investigate AITs in depth. It starts with a thorough selection of trustworthy online libraries as primary sources, such as IEEE, Web of Science, ScienceDirect, and Springer. Specific research questions (RQs) are then developed to lead the investigation, and relevant keywords are picked to narrow the search. Firstly, publications between 2000 and 2022 are selected, and a thorough screening process is conducted, including title and abstract evaluations, data extraction, quality review, and meticulous data analysis. Secondly,

the overview of AITs contextualizes the ensuing study and then digs into case studies focused on Thailand to provide localized insights. The evaluation systematically addresses the RQs, ending in the strategic selection and recommendation of AITs customized to Thailand's situation. This scientific methodology strengthens the study's credibility and broadens the understanding of AITs in Thailand. The following methodology was adopted to review the literature.

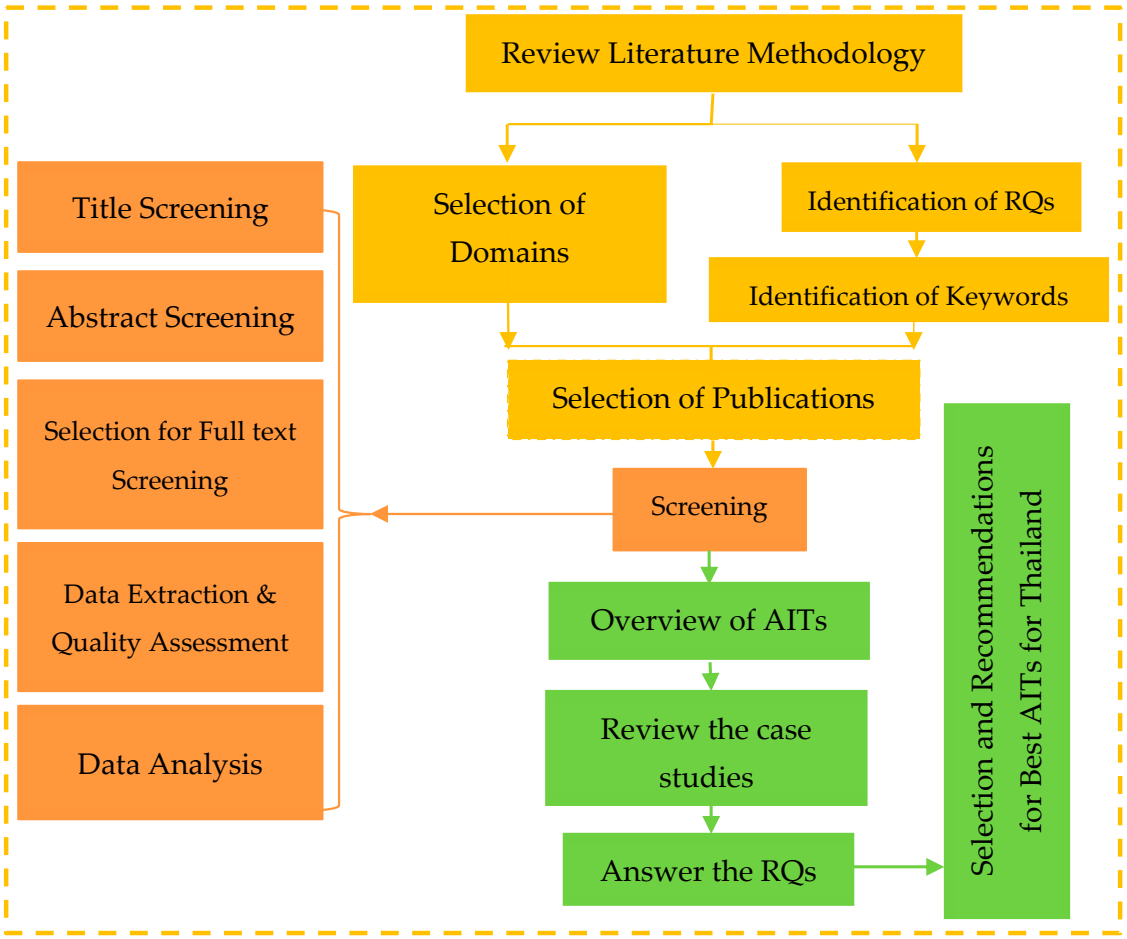


Figure 1. Methodology for Review Literature.

2.1. Research Questions (RQs)

RQs were designed to reflect the investigation goals. According to the stated problems and objectives of the proposed investigation, the following RQs have been proposed: (1) What past methods have been used or proposed for rainfall forecasting, and how are these forecasting techniques' effectiveness evaluated? (2) What influencing variables (meteorological data like humidity, direction, temperature, and wind speed) can be applied to predict seasonal rainfall most efficiently? (3) What dataset is used for forecasting, for which study area is the rainfall forecast generated, and which variables influence the precision of long- and short-term and seasonal rainfall predictions? (4) What are the most recent study trends in rainfall forecasting? (5) Are AIT forecasts more accurate than traditional forecasting models? Could AITs be an appropriate alternative to the complicated forecasting models that are currently used? What is the best approach for choosing input variables for maximum accuracy? (6) Are AITs' forecasts better than the existing forecasting models? Could AITs represent a possible alternative to the existing complex forecasting models?

2.2. Keywords Selection

The next step is to create the query string, which can be conducted in this manner. The RQs were initially scanned for keywords and arranged to generate a query in a preset order. The keywords from the query include Modified, Customized, Combined AITs, Approaches, Techniques, Algorithms, Rainfall, Estimation, Predicting, Modelling, Performance, Assessment, and Evaluation.

The completed query string is presented here in its entirety:

(Performance AND Evaluation OR Evaluation) "Data Mining" AND "Methods" OR "Techniques" OR "Machine learning" AND "Rainfall" AND ("Forecasting" OR "Prediction" OR "Assessment"). "Rainfall" AND "Forecast" OR "Projection" OR "Estimate."

2.3. Domains Selection

This stage involves selecting libraries using a query string. Well-known online libraries such as IEEE, Web of Science, ScienceDirect, and Springer were selected for this review. Query strings were modified to retrieve the most relevant literature from these libraries, offering distinct search options. Many keyword combinations were used in the query.

2.4. Defining Selection Conditions

The purpose of this step is to draw out the selection boundaries to select the research papers that are the most pertinent. This undertaking is divided into the inclusion conditions (ICs) and the exclusion conditions (ECs).

2.5. Inclusion Conditions (ICs)

This investigation adheres to the following ICs rules: (1) Publications dated between 2000 and 2022; (2) Publicly accessible journal articles, conference proceedings, or workshop proceedings; (3) Publications that use AITs to forecast rainfall; (4) Publications that compare strategies for data mining and rainfall forecasting; (5) Publications that present enhanced or customized AITs to forecast rainfall; and (6) articles that integrate AITs with any other technique.

2.6. Exclusion Conditions (ECs)

The norms of exclusion criteria are as follows: (1) Documents not written in English; (2) Articles published between 2000 to 2022. A few reference studies, i.e., the development of the model and methodology, were also considered without the timeframe limit; (3) Articles that did not forecast rainfall; (4) A paper that makes no use of weather observation data in its predictions; and (5) Articles that did not analyze the performance of the employed/suggested method.

2.7. Literature Extraction

The selection criteria are designed to collect the most pertinent data items used for analysis. The final shortlist of 40 articles was determined after considering both the ICs and the ECs.

2.8. Quality Evaluation

Committing to quality standards while conducting reviews is necessary to accomplish the study's goals. Detailed procedures were carried out to guarantee a high standard of results: (1) To acquire research articles, credible and genuine online libraries were selected; (2) The recent research papers were selected to ensure the results accurately reflect the most recent findings; (3) The selection process was carried out fairly; and (4) Every aspect of the review process was carried out meticulously and accurately.

3. Developments in Rainfall Forecasting Methods

Ashok (2022) provides an overview of the progress of rainfall forecasting systems from 1900 to the present and the primary approaches utilized during various periods. There

was a steady transition from statistical methodologies before 2000 to process-based big advanced statistics and the Internet of Things for improved forecasting today [20]. The development of rainfall forecasting techniques and the required input data are illustrated in Table 1. It provides a detailed breakdown of the development of rainfall and weather forecasting methods. It is divided into three sections: before 2000, after 2000, and the current period. Before 2000, from 1900 to 1940, only correlation, multiple regression, and frontal analysis were practiced. In the second section, from 1941 to 2000, scientists and water resource engineers made many developments, and they presented stochastic methods, power regression models, and NWP models. This was only achievable because of advances in real-time weather data observations and significant computing advances, such as the creation of supercomputers. However, the data requirements and high-computational processing systems were the main problems with these models. These problems were solved in the current section by the advanced algorithms in ML and DL models, which results in fast and accurate rainfall and other weather forecasting. This research focuses primarily on seasonal rainfall forecasting over different climatic regions of Thailand. In the next sections, ML and DL models are discussed in detail.

Table 1. The developments in rainfall forecasting methods [20].

Duration		Methodology	Input Data
Before 2000	1900–1940	Surface measurements Graphs and maps for estimating pressure contours	The correlation coefficients method Frontal evaluation Multiple regression solutions
	1941–2000	Application of aircraft to acquire meteorological data in real-time. Popularization of radar and satellite observations Utilization of marine surface temperature and average sea level pressure Statistical information on zonal or meridional winds	Upper-level waves/air were correlated with surface pressure patterns. From 1981 to 1990, the focus was on stochastic methods for long-range forecasting. Power regression models NWP models
After 2000	2000–2017	Ground-based/weather satellites Large-scale radar network deployment	Meteorological development Utilization of high-speed computing facilities rainfall forecast through Radar Introduction of ML and DL models
Current	2017–2022	Work on efficient and quick algorithms The big data and IoT era for rainfall prediction Examined the impact of rainfall on numerous meteorological variables. Efforts to enhance forecast precision	Emphasis on data collection with a substantial spatial and temporal resolution The wholly wireless and automatic data collection system Advancement in radar data

4. Application of AI Techniques in Rainfall Forecasting (Worldwide)

Various AITs, including ANNs, support vector machine (SVM), and Fuzzy logic (FL), have been employed for rainfall forecasting. These techniques have been used to model the relationships between meteorological variables and rainfall and to predict future rainfall based on historical data. Many recent studies have employed AITs for rainfall forecasting and have achieved promising results [21,22]. Due to their ability to recognize complex patterns, record non-linear correlations, and handle vast amounts of meteorological data, AITs are extremely useful in rainfall forecasting. AITs increase the accuracy and adaptability of forecasts by iteratively improving predictive models, taking into account complex and dynamic meteorological events. Informed decision-making, effective resource allocation, proactive disaster preparedness, and ideal risk mitigation across several sectors are all made possible by this skill, which depends on precise rainfall estimates [22]. AITs have improved

the accuracy of rainfall forecasts [23]. Recent studies have shown that AI techniques can capture complex non-linear relationships between meteorological variables and rainfall and perform better than traditional statistical models and ML techniques [24,25]. AI is a vast and inclusive domain in which ML is a distinct subfield. ANNs are a more specialized branch of ML, while DL emerges as a sophisticated and intricate component as one delves deeper into this framework. The relationship between AITs, ML, ANN, and DL is shown in Figure 2.

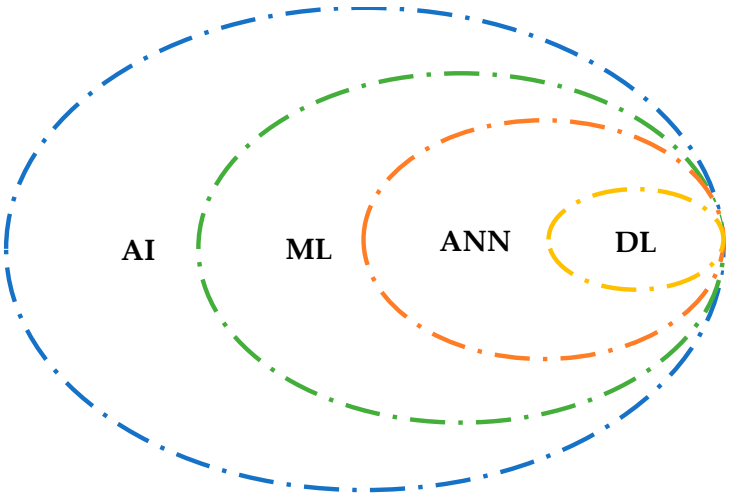


Figure 2. Relationship between AI, machine learning, artificial neural networks, and deep learning.

4.1. Machine Learning

ML is part of AI, which consists of algorithms that can be automatically trained and analyzed to build accurate models from specific datasets. The classification AI consisting of ML and DL is presented in Figure 3. Figure 3 depicts the hierarchical classification emerging within the ML field, embracing supervised, unsupervised, semi-supervised, and reinforcement learning methods. The commonly used supervised and unsupervised methodologies are particularly relevant to rainfall forecasting. After that, the supervised approach is subdivided into regression and classification, which are further subdivided into decision trees (DT), random forests (RFs), ANNs, DL, SVM, K-Nearest Neighbors (KNN), and Bayesian methods. Notably, a finer classification occurs within the domain of DL, separating feed-forward neural networks (FFNN), wavelet neural networks (WNNs), deep neural networks (DNNs), convolutional neural networks (CNNs), and recurrent neural networks (RNNs) as distinct subcategories. Unsupervised ML, on the other hand, is divided into two categories: clustering methods, which include k-means, hierarchical, and fuzzy c-means, and dimensionality reduction techniques, which include singular value decomposition (SVD, principal component analysis (PCA) and independent component analysis (ICA). This sophisticated hierarchy of classifications provides a thorough framework for understanding the numerous disciplines and subfields within AI and ML, laying the groundwork for later study and analysis in the context of rainfall forecasting.

Various rainfall forecasting applications have utilized supervised learning, including short- and long-term weather prediction, flood forecasting, and drought surveillance. Unsupervised learning is a technique for ML wherein the algorithm learns from the nature of datasets. Without prior knowledge of the outcome, the algorithm discovers connections and patterns within the data [26]. Due to their ability to discover relationships and patterns from data, ML algorithms are a popular option for rainfall forecasting. ML models have been applied to forecasting short- and long-term rainfall [27]. The following section presents an overview of all supervised ML and DL techniques.

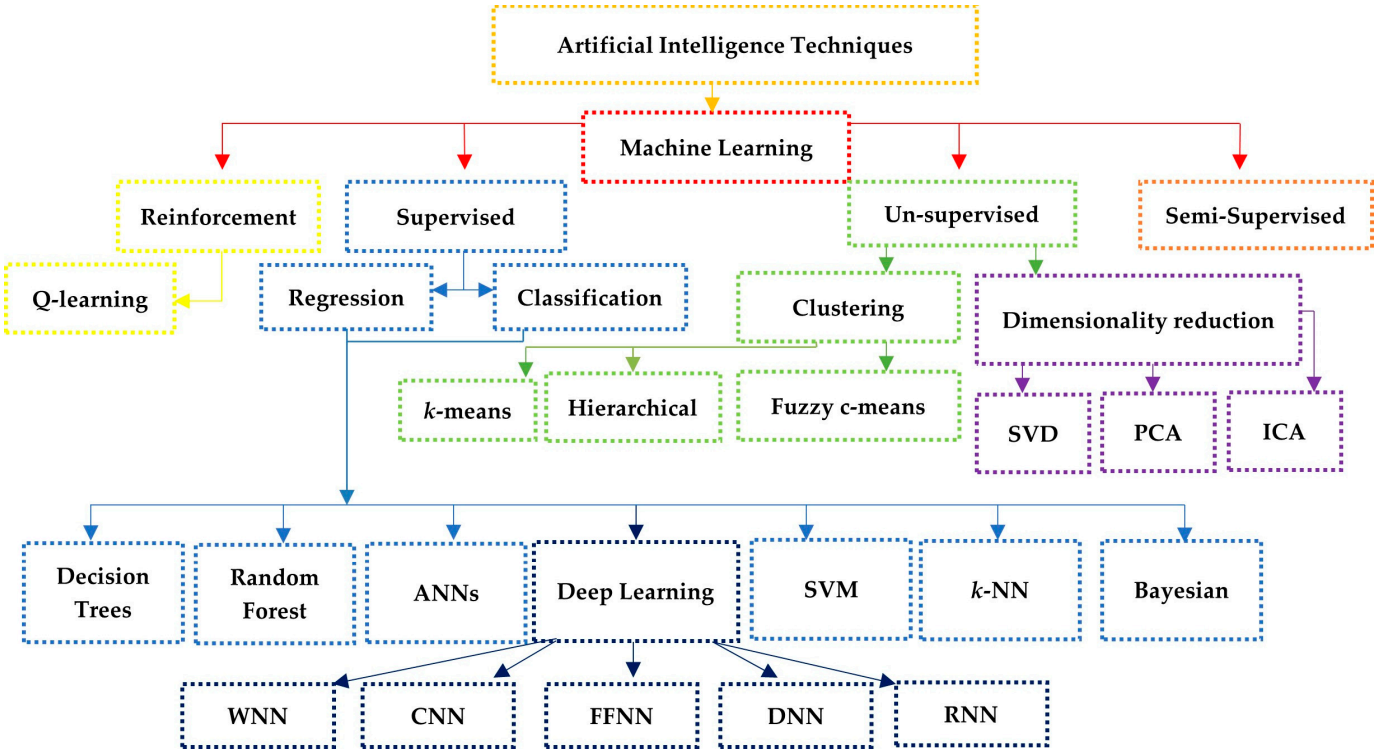


Figure 3. Classification AITs, including ML and DL.

4.1.1. Support Vector Machines (SVMs)

SVMs rely on supervised learning algorithms for classification, time series, and regression analysis. Due to their capacity to deal with complex connections between factors and noisy data, SVMs have been extensively employed for rainfall forecasting. SVMs function by mapping datasets of higher-dimensional space and locating a hyperplane that divides data points into distinct classes [28]. A SVM was proposed by [29] to overcome the obstacles related to prediction. ANNs aim to lower training errors, whereas SVMs aim to reduce generalization errors. These techniques accomplish the utmost achievable level of accuracy in their disciplines. Compared to ANNs, SVMs are based on structure-based risk minimization instead of empirical risk minimization. The SVM basic operation is demonstrated in Figure 4. The SVM approach follows a logical progression: (1) inclusion of the input dataset; (2) iterative examination of various model compositions involving predictor and target variables; (3) execution of training and testing stages; (4) selection of an appropriate kernel function; (5) accommodation of multi-class scenarios through diverse constraint combinations; and (6) use of v-fold cross-validation to ensure robust testing and validation. Finally, the process results in: (7) identification of the most capable SVM model through extensive v-fold cross-validation, producing informative results for display and analysis [25].

Support Vector Regression (SVR) is a subset of SVMs used for regression analysis. Numerous studies have used SVR for rainfall forecasting, including Vafakhah et al. (2020). The authors used SVR to forecast daily rainfall in Iran. The study discovered that SVR outperformed the conventional methods, including multiple linear regression and ANNs [30].

Multi-Kernel SVR is a variation of SVR that uses multiple kernel functions to detect various data patterns [31]. Numerous studies have used it for rainfall forecasting, including Caraka et al. (2019), who used multi-Kernel SVR seasonal autoregressive integrated moving average (MKSVR-SARIMA) to forecast daily rainfall in Manado, North Sulawesi provinces in Indonesia. The study revealed that MKSVR-SARIMA excelled over other conventional techniques [32].

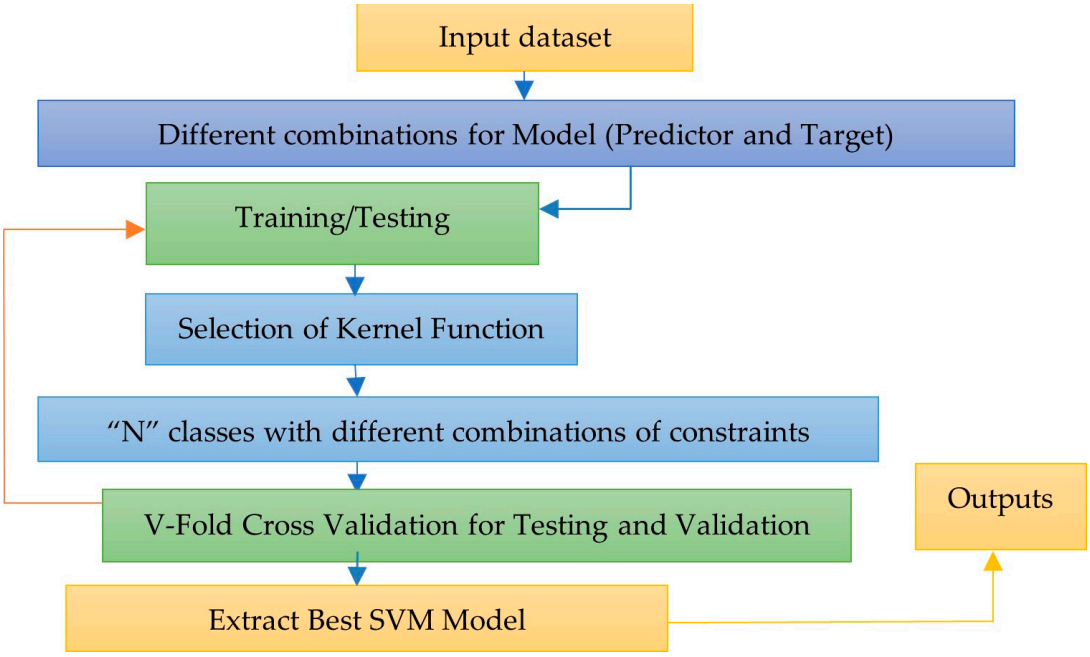


Figure 4. Schematic representation of SVM [25].

A SVM with a Firefly Algorithm (SVM-FA) is a type of SVM that employs the FA, a meta-heuristic optimization algorithm, for fine-tuning the SVM model's parameters [33]. Numerous studies have used the SVM-FA for rainfall forecasting, including Danandeh Mehr et al. (2019), who used the SVM-FA hybrid model for monthly rainfall in northwest Iran. The findings determined that SVM-FA outperformed its competitors with a 30% reduction in root means square error (RMSE) and a 100% boost in Nash-Sutcliffe efficiency (NSE). The authors recommend this model for monthly rainfall in semiarid regions [34].

SVMs have proven useful in rainfall forecasting but have several limitations. These limitations include their sensitivity to parameter selection, limited interpretability, limited handling of missing data, limited handling of non-linear relationships, limited scalability, and limited handling of multiple outputs [35]. To overcome these limitations, researchers may need to develop new techniques to improve the interpretability of SVMs, handle missing data and non-linear relationships more effectively, and develop new approaches to handle large datasets and multiple outputs. Overall, SVMs remain a valuable tool for rainfall forecasting, but they should be employed in conjunction with other machine learning algorithms to capture the full range of relationships between variables [35].

4.1.2. Decision Trees (DTs)

DTs have been used for rainfall, flood forecasting, and drought monitoring [24,36]. Figure 5 depicts the process of DTs, as described by Humphries et al. (2022): data separating and error eradication proceed until the terminal node is reached or the dataset misclassification error at the termination of the terminal node becomes zero. At this point, further data splitting will discontinue. The output value is displayed on the terminal node generation's display [36].

For instance, Dou et al. (2019) analyzed and contrasted the efficacy of two cutting-edge machine learning models, DT and random forest (RF) technology, to model the massive rainfall-triggered landslide events in the Izu-Oshima Volcanic Island, Japan, on a regional scale. The RF and DT models can be utilized in similar non-eruption-related landslide investigations in tephra-rich volcanoes because they can rapidly generate precise and stable LSM maps for threat management and decision-making [37].

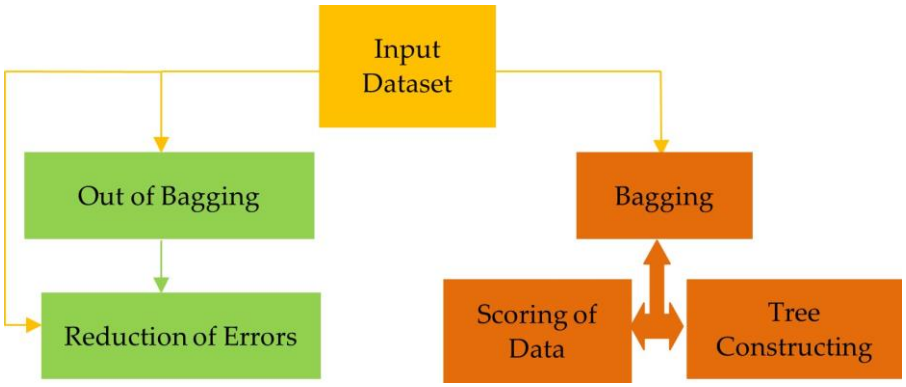


Figure 5. Flow Diagram of Decision Tree Forest [36].

In Pakistan's Mangla watershed, Humphries et al. (2022) used decision tree forests, tree boosts, and solitary decision trees to estimate the rainfall runoff. The authors used meteorological records like the temperature, humidity, and runoff datasets to forecast rainfall runoff. The results indicated that the decision tree could forecast the rainfall-runoff process more precisely than the other methods [36].

In another study, Ahmadi et al. (2022) propose a new sequential minimal optimization (SMO) that develops ensembles for rainfall prediction utilizing random committee (RC), Dagging (DA), and additive regression (AR) models. In Kermanshah, Iran, a synoptic station was in operation between 1988 and 2018, and they collected thirty years' monthly datasets, including the highest and lowest relative humidity rates, temperatures, evaporation data, sunlight hours, wind speed, and rainfall. This study demonstrated that the DA-SMO ensemble algorithm outperformed the others [38].

Gulati et al. (2016) mentioned that DTs have limitations, including overfitting, instability, and bias. Researchers may need to develop new techniques to defeat the limits and enhance the accuracy and robustness of DTs in prediction applications [39].

4.1.3. Random Forest (RF)

RF is a powerful ML algorithm widely used in various fields, including rainfall prediction [40]. RF is a technique for ensemble learning which utilizes multiple decision trees to make precise predictions [41]. RF has been utilized in several aspects of rainfall forecasting, including rainfall estimations, drought prediction, and flash flood forecasting. Using Malaysian data, Zainudin et al. (2016) investigated a variety of classifiers to forecast rainfall, including Nave Bayes, SVM, DT, ANNs, and RF. The results showed that RF outperformed the other ML algorithms [40].

In another investigation, Pham et al. (2019) compared linear discriminant analysis (LDA), RF, and support vector classification for rainfall-state classification. The results indicate that RF is superior to LDA and SVC for classifying rainfall states. Using RF for three-state rainfall classification and LS-SVR for rainfall-amount forecasting can enhance the downscaling of extreme rainfall [42].

The objective of the proposed research by Primajaya and Sari (2018) was to establish a model utilizing the RF algorithm. The application of RF on the training set resulted in a model with an accuracy of 71.09%. An f-measure of 0.79, recall of 0.85, and precision of 0.75 further demonstrate the model's performance. The kappa statistic is 0.33, with a mean absolute error (MAE) of 0.35 and a root mean squared error (RMSE) of 0.46 for the model. Furthermore, the receiver operating characteristic curve (ROC) area is 0.78, demonstrating the resilience of the RF method. Implementing the RF algorithm with 10-fold cross-validation produced output with an accuracy of 99.45%, precision of 0.99, recall of 0.99, f-measurement of 0.99, kappa statistic of 0.99, MAE of 0.09, RMSE of 0.14, and ROC area of 1 [43].

RF is a powerful ML algorithm that is extensively employed in rainfall forecasting. Nonetheless, RF has limitations, such as a lack of interpretability, limited support for multi-

ple outputs, and restricted scalability. Researchers may need to develop new techniques to enhance the interpretability of radio frequency (RF) data and more effectively manage multiple outputs and large datasets [44].

4.1.4. Artificial Neural Networks (ANNs)

ANNs are commonly implemented in rainfall forecasting. ANNs have been implemented in numerous applications. The ANN model attempts to link the data inputs and the outputs projected for the forthcoming period without employing predefined coding. It is suitable for weather forecasting because of the random and unpredictable nature of the weather's characteristics and the intricate nature of the systems [45]. This network has three layers, as shown in Figure 6: output, input, and hidden layers.

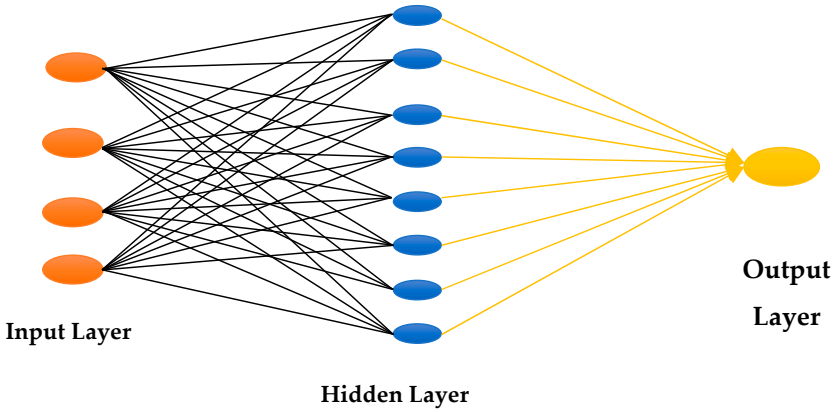


Figure 6. Schematic representation of ANN.

Hsieh et al. (2019) employed a hybrid model of ANN and multiple regression analysis (MRA) to predict the total typhoon rainfall and groundwater-level rise in the Zhuoshui River basin. Using data from gauge stations in eastern Taiwan and open-source typhoon data, the authors constructed an ANN model to predict the total rainfall and groundwater level during a typhoon encounter; they then revised the predictive values using MRA. The results demonstrated that the ANNs accurately and dependably predicted rainfall [46].

Hossain et al. (2020) assessed the effectiveness of MLR and ANN in modeling long-term seasonal rainfall patterns in Western Australia. The oceanic climate variables El Niño Southern Oscillation and Indian Ocean Dipole were viewed as potential seasonal rainfall forecasters based on their time series data. The methodologies were utilized at three Western Australia rainfall stations. As expected, the ANN models outperformed the MLR models regarding the Pearson correlation and statistical error when estimating Western Australia's spring rainfall [47].

ANNs have limitations, including overfitting, computational complexity, and interpretability. Researchers may need to develop new techniques to improve the interpretability of ANNs and handle large datasets more effectively. Overall, ANNs remain a valuable tool for rainfall forecasting, and their applications will likely expand [48].

4.1.5. K-Nearest Neighbors

A supervised ML algorithm *k*-NN can handle classification and regression problems. The *k*-NN algorithm assigns data points to the same class when they are close together, or there is an obvious distinction between classes. *k*-NN uses the Euclidean distance formula to determine the distance between two graph nodes. An advantage of *k*-NN for rainfall data is that record points can be quickly trained and categorized with minimal tuning [49]. It is shown in Figure 7.

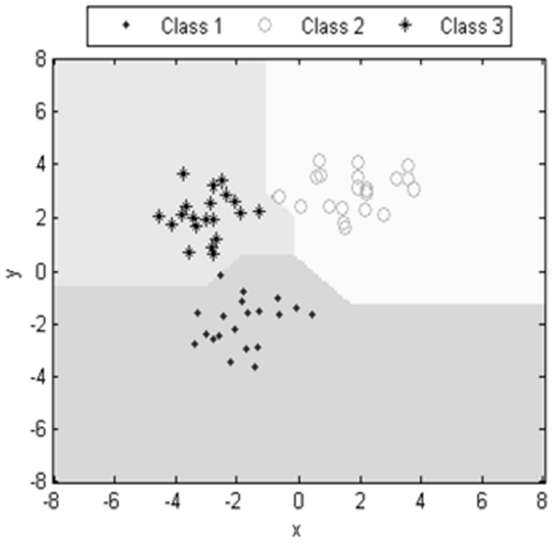


Figure 7. Simple *k*-NN classifier [49].

k-NN has been used for various aspects of rainfall forecasting. Wu et al. (2010) utilized *k*-NN to predict extreme rainfall events in China's Pearl River Basin. The authors predicted extreme rainfall events using meteorological variables. The results indicated that *k*-NN could predict extreme rainfall events with excellent precision and efficacy [50].

Using pattern similarity-based models and the *k*-NN technique, Sharma and Bose (2014) forecasted the monthly rainfall based on historical data to compare the predicted values with the observed data. They utilized a recently proposed method for rainfall forecasting, Approximation, as well as Prediction of Stock Time-series Data (APST). In addition, they presented two variants of the APST. These techniques are superior to the original APST and AR models [51].

k-NN has limitations, including the choice of K, computational intensity, and sensitivity to outliers. Researchers may need to develop new techniques to overcome these limitations and enhance the accuracy and robustness of *k*-NN in rainfall forecasting applications [52].

4.1.6. Bayesian Methods

Bayesian methods have been increasingly applied in rainfall forecasting due to their ability to integrate prior knowledge and uncertainty in the modeling process [53]. Various aspects of rainfall forecasting have utilized Bayesian methods. For example, Nikam and Meshram (2013) used an anticipated and implemented data-intensive model in conjunction with data mining to predict rainfall resources. They utilized a Bayesian method and discovered it to be effective and accurate. The study demonstrated that Bayesian models could predict rainfall with high precision and accuracy [53].

Khan and Coulibaly (2006) proposed a Bayesian method for training a multilayer feed-forward neural network (FFNN) for generating reservoir inflow and daily river flow in a Canadian river basin. The Bayesian neural network (BNN) model worked better than the theoretical model and performed marginally better than the conventional ANN model when simulating peak, mean, and basin inflows and low river flows. It is demonstrated that BNN models provide accurate reservoir inflow and streamflow forecasts without sacrificing model forecast precision when matched to a conventional ANN and the proposed framework Hydrologiska Byråns Vattenbalansavdelning (HBV) model. The Bayesian learning algorithm automatically manages overfitting and underfitting, which are serious problems with traditional ANN learning algorithms. This is a significant advantage of the BNN approach [54].

Kaewprasert et al. (2022) computed credible and highest posterior density (HPD) estimates for the average and alteration among the means of delta-gamma distributions and a confidence interval based on fiducial values using Bayesian technique based on

Jeffrey's rule and uniform priors. Based on the simulation outcomes, the Bayesian HPD predicted the shortest duration and performed well regarding coverage probability. Rainfall statistics from the Chiang Mai region of Thailand demonstrate the suggested technologies' effectiveness [55].

Bayesian methods also have limitations, including computational complexity, the choice of the prior distribution, and model complexity. Researchers may need to develop new techniques to overcome these limitations and enhance the accuracy and robustness of Bayesian methods in rainfall forecasting applications [56].

4.2. Deep Learning

DL is a subcategory of supervised ML. DL employs multi-layered data learning methodologies. These layers are arranged using non-linear modules to obtain the optimal solution with the least loss [8]. The information processing and communicating processes are based on human nerves [9]. DL's primary job is to analyze and extract characteristics from datasets to generate accurate models. DL applications include image analysis and processing, natural language processing, handwriting identification, social media sentiment analysis, and prediction and forecasting. The universal architecture of deep neural networks is illustrated in Figure 8.

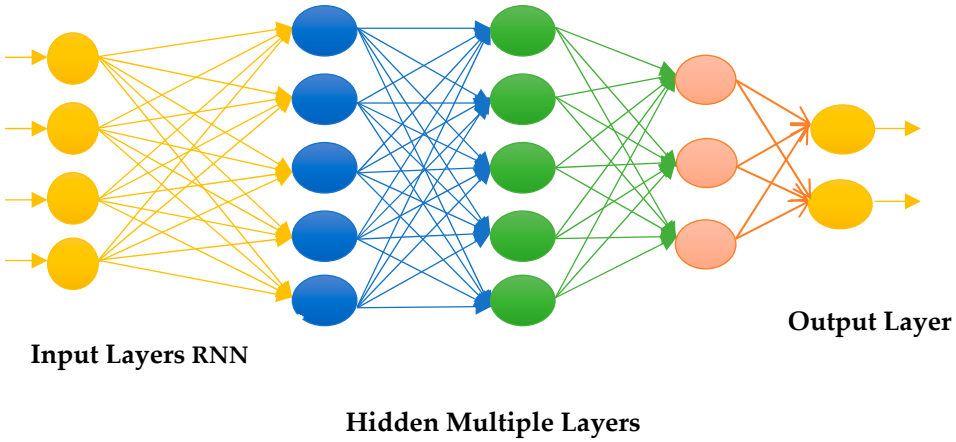


Figure 8. Architecture of Deep neural networks.

4.2.1. Convolutional Neural Networks (CNNs)

The CNN is a deep neural network commonly used for image recognition, but it is also employed for time-series forecasting problems. The CNN is designed to automatically learn characteristics from input data by applying convolution and pooling operations. Convolution is the process of extracting local attributes of the input data and pooling them to reduce the dimensionality of the data. By stacking multiple convolutional and pooling layers, the CNN can learn hierarchical features from the input data and generate predictions [57].

Figure 9 illustrates that Narejo et al. (2021) employed a modified form of the CNN to the time series estimation task for the eight-day ahead prediction rainfall series. Three filters with a kernel size of (3, 1) were used. The first and second convolution layers contain ten filters of the same dimensions (3, 1). Following the "average" methodology for subsampling, the pooling layer was added. In this instance, however, the average factor was one. The tangent hyperbolic activation function was used for entirely connected layers, followed by a linear layer for output predictions. The authors utilized MSE to determine the most accurate forecasting model. The authors' proposed model yielded encouraging results [58].

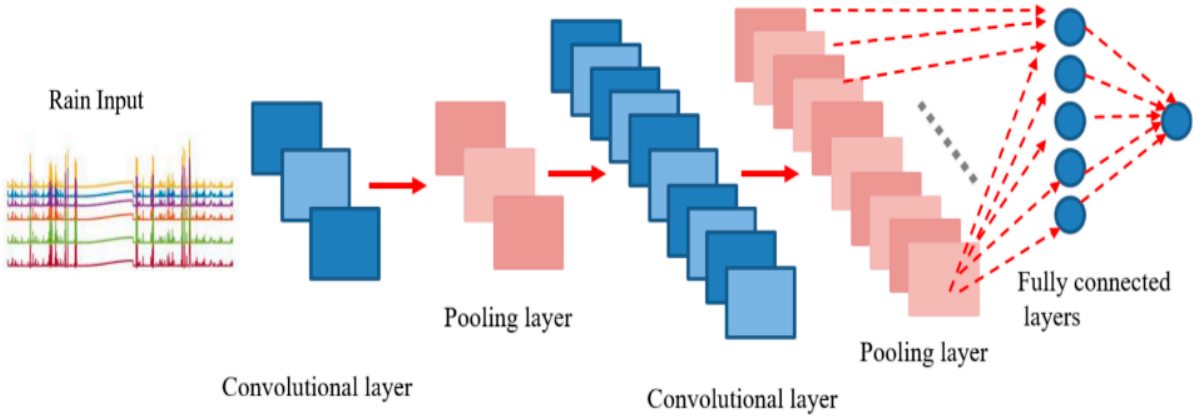


Figure 9. CNN architecture for eight steps ahead of rain forecasting [58].

Recent studies employing the CNN for rainfall forecasting have yielded promising results. Elhoseiny et al. (2015) investigated how the CNN could identify weather from images and assessed the identification output of the ImageNet-CNN and weather-trained CNN layers. The model outperformed the most recent weather classification technology by a wide margin. They also examined the behavior of all CNN layers and uncovered some intriguing results [59].

Using climate data, Liu et al. (2016) showed that deep learning could predict extreme weather patterns. A CNN architecture with a high depth level was devised to identify tropical cyclones and atmospheric rivers. This optimistic implementation may resolve multiple pattern detection issues in climate science. The DNN produces high-level algorithms directly from the data, thus preventing the use of subjective conventional adaptive threshold criteria for detecting climate-dependent events. The outcomes of this investigation are used to assess the current and potential developments in climate extreme weather events and investigate changes in the thermodynamics and dynamics of such events as an outcome of global warming [60].

The CNN has some drawbacks, such as its need for a large quantity of data and its black-box nature. Nonetheless, with the increase in the availability of weather information and the creation of novel interpretability techniques, the CNN has great potential in rainfall forecasting [61].

4.2.2. Feed-Forward Neural Networks (FFNNs)

The FFNN is a form of ANN commonly applied to time-series forecasting issues. An input layer, one or more concealed layers, and an output layer comprise the FFNN. Each layer comprises one or more interconnected neurons with neurons in the layer beneath it. Setting the connection weights among neurons within each layer, the FFNN learns to forecast the output [62]. In Figure 10, a FFNN is presented for rainfall forecasting.

Recent research has used FFNNs for rainfall forecasting with promising results. Paras et al. (2009) forecasted relative humidity and maximum and minimum temperatures using time series analysis. A back-propagation multilayer FFNN was used. They found FFNNs to be superior to other methods, with better results [64].

Velasco et al. (2019) developed a week-ahead rainfall forecast employing a multilayer perceptron neural network (MLPNN) to assess historic rainfall records. After model installation, data preparation, and performance assessment, two MLPNN models predicted the rainfall in the following weeks. The MLPNN supervised the FFNN with 11 input neurons indicating meteorological data, concealed neurons, and seven output neurons indicating the week's forecast. Sigmoid transfer function (SCG) and SCG-Tangent MLPNN models had MAE and RMSE of 0.0127 and 0.1388, or 0.01512 and 0.01557, respectively [65].

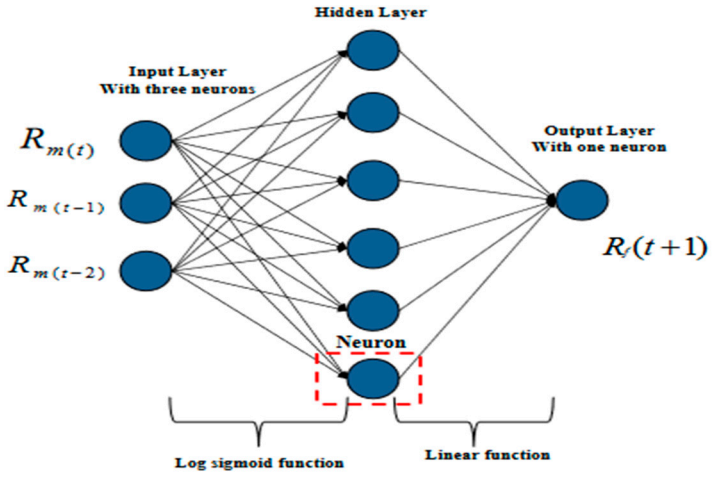


Figure 10. Feed Forward Neural network model architecture utilized for rainfall forecasting [63].

Recent studies demonstrated that the FFNN could capture complex data relationships and accomplish them better than traditional statistical models [63–65]. The FFNN does, however, have significant drawbacks, including overfitting and being a black-box model. However, with the expansion of rainfall data and the creation of new interpretability tools, such as the use of feed-forward in predicting rainfall, ANNs have much potential [66].

4.2.3. Recurrent Neural Networks (RNNs)

A subset of ANNs called an RNN is designed to handle sequential data, such as time-series data. In contrast to feed-forward neural networks, which analyze each input independently, RNNs contain a memory component that enables them to keep account of earlier inputs in the sequence. Therefore, they are ideally adapted for activities like rainfall forecasting, where the current prediction relies on earlier measurements [67].

RNNs, unlike traditional ANNs, have connected neurons in recurrent layers (Figure 11). Thus, information from a neuron is conveyed to neurons in similar layers above or below. As depicted in Figure 9, RNNs also contain a concealed state for recalling sequence data. RNNs approximate new states by recursively applying activation functions to previous states and new inputs.

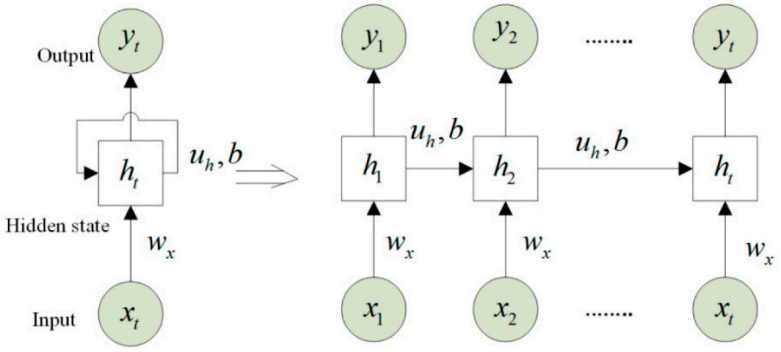


Figure 11. Architecture of a recurrent neural network [68].

The RNN is an efficient model for time series forecasting because its feedback connections can transmit information from one input to the next, simulating the dynamic behavior of the data sequence. However, a straightforward or shallow RNN frequently faces the issue of gradients that vanish. It cannot simulate long-term trends and impairs the network as a result. The gradient-diminishing issues in RNNs have been addressed in recent years by the more expensive long short-term memory (LSTM) neural network [68].

Many recent research investigations have used the RNN to predict rainfall with promising results. Dong et al. (2021) forecasted the daily average air temperature of the

four (RNNs) using a model which incorporates convolutional neural networks (CNNs) and RNNs. Between 1952 and 2018, the convolutional recurrent neural network (CRNN) was trained using daily air temperature measurements over China. Using historical air temperature data, their model could precisely predict the air temperature [69].

Similarly, Poornima and Pushpalatha (2019) introduced an Intensified LSTM-based RNN for predicting rainfall. The neural network is proficient and was evaluated by applying a standard rainfall record. The network was trained to forecast the characteristics of rainfall. The precision, epochs number, loss, and network learning rate are considered when assessing the performance and efficacy of the planned rainfall prediction model. The results are compared to the Holt–Winters, Extreme Machine Learning, autoregressive integrated moving average (ARIMA), LSTM, and RNN models to illustrate the improvement in rainfall forecast [4].

Utilizing RNNs to improve the accuracy of rainfall forecasts is a prospective research topic. Recent research has demonstrated that RNNs outperform conventional statistical approaches and FFNNs, indicating that they capture better complex non-linear correlations in the data. However, RNNs have disadvantages, such as the prospect of gradients vanishing or exploding and the need for expensive computation [67].

4.2.4. Deep Neural Networks (DNNs)

Due to DNNs' ability to process big datasets and learn complicated non-linear correlations, DNNs have become a useful tool for time-series forecasting tasks. DNNs are superior to shallow neural networks (SNNs) because of their ability to learn more complex data representations, making them useful for tasks like rainfall forecasting, where the connections between meteorological parameters and rainfall can be highly non-linear [70].

Recent DNN rainfall forecasting tests have yielded promising results. Weesakul et al. (2021) tested machine learning's monthly rainfall forecasting using DNN. Due to its long-term rainfall data, the Ping River basin in northern Thailand was chosen for the study. The monthly rainfall between 1975 and 2018 was analyzed at six river basin rainfall sites. The efficacy of the model was evaluated using the stochastic efficiency (SE) and correlation coefficient (r). According to previous research, the 24 large-scale atmospheric variables (LAV) employed as predictors in the DNN model associated relationships with seasonal rainfall in the Ping River basin. The initial simulation utilizing all 24 LAV of the validation period (2009–2019) to estimate the six-month rainfall in stations one year in the future demonstrates that the DNN can make predictions with an accuracy range of 58% to 72% and a correlation coefficient of 0.59 to 0.80. The input selection enhanced the prediction by decreasing the input LAV range from 24 to 13. In the next simulation with input selection, the DNN provided more accurate one-year forecasts with stochastic efficiencies ranging between 69% and 78% and correlation coefficients ranging, in all stations, between 0.75 and 0.82 [27].

Barman et al. (2021) evaluated the use of linear regression, SVR, and DNN for rainfall forecasts in Guwahati. The study utilized the daily rainfall data from Guwahati, Assam, India. Daily meteorological data were used in this study. The RMES, MAE, and MSE were compared with the DNN, LR, and SVR. The MSE and RMSE are lower for the DNN model than for the LR and SVR, but the SVR outperforms MAE. Regardless of the proportion of trainings to test rainfall statistics, both models are superior [71]. DNNs could improve rainfall forecasts. Recent research has demonstrated that DNNs can learn complicated non-linear correlations in data and outperform statistical models and other neural network architectures. DNNs can overfit and are computationally expensive [70].

4.2.5. Wavelet Neural Networks (WNNs)

WNNs are a wide range of ANNs that model time series data by combining wavelet analysis and neural networks [72]. WNNs use wavelet analysis and neural networks to model time series data. Time series data is decomposed using wavelet analysis to create several frequency bands, each of which can be utilized to detect unique patterns [73].

Recent studies have utilized WNNs extensively for rainfall forecasting, with promising results. Different models evaluated by Estévez et al. (2020), which combine wavelet analysis (multiscalar decomposition) and ANNs, have been tested on sixteen sites across southern Spain (Andalusia region, which is semiarid), each representing a climate and landscape that is distinct from the others. Ten WNNs were deployed to forecast the monthly rainfall, and were evaluated using short-term thermo-pluviometric time series. This is conceivable due to the competence of wavelets to characterize non-linear signals. Although each of the evaluated sites had satisfactory results, there are discrepancies between the forecasts of the ten models [73].

Wang et al. (2017) developed a WNN-based model for daily rainfall forecasting using meteorological data. They used the Discrete Wavelet Transform (DWT) to split the weather data into different frequency bands and then taught a neural network the relations between the decomposed signals and the rainfall. They performed more effectively than conventional statistical models and other neural network architectures [74].

Similarly, Venkata Ramana et al. (2013) attempted to discover an alternate solution for rainfall forecasting by merging the wavelet technique and ANN. The WNN models were applied to the Darjeeling rain gauge station's monthly rainfall data. Statistical methods were employed to assess the validation and calibration performance of the models. The results of modeling the monthly rainfall series indicate that WNNs are more effective than ANN models [75].

Partal et al. (2015) investigated three different NN algorithms (feed-forward back-propagation, FFBP; radial basis function; generalized regression neural network) and wavelet transformation for predicting daily rainfall. Various input combinations for rainfall estimation were evaluated. Consequently, the optimal neural network model was determined for each station. In addition, the effectiveness of linear regression models and wavelet neural network models are compared. It was discovered that the wavelet FFBP procedure provides the superlative performance assessment criteria. The findings designate that the coupling wavelet alters with neural networks that deliver significant estimation process advantages. In addition, the worldwide wavelet spectrum delivers essential evidence regarding the physical process being modeled [76].

WNNs also have some drawbacks, including computational expense and the possibility of overfitting. However, with novel training techniques and hardware, WNNs have tremendous potential in rainfall forecasting [73,77].

Overall, Table 2 presents the different advantages and disadvantages of ML and DL for rainfall forecasting. SVMs excel at managing complex data and preventing overfitting, but they can be difficult to interpret and struggle with missing data. DTs are effective for real-time forecasting, although they are susceptible to overfitting and biases. RF can handle non-linear correlations and missing data but lack interpretability, whereas ANNs can handle non-linear patterns but face issues such as overfitting and computational complexity. Deep Learning technologies, such as CNNs, improve the accuracy but require a large amount of data and lack transparency. WNNs show potential in managing big, non-linear data for rainfall prediction but still require safeguards against overfitting. RNNs can handle sequential data but face gradient problems, while RNNs can handle sequence data but encounter gradient problems. By processing vast amounts of meteorological data, identifying intricate patterns, and developing flexible ML and DL models, AITs significantly improve rainfall predictions. Ultimately, these AITs enable better resource allocation, risk mitigation, and disaster preparedness, resulting in cost savings, effective resource management, and increased societal resilience.

Table 2. Strength and Weakness of AITs in terms of Rainfall Forecasting.

	AITs	Advantages	Disadvantages	Reference
Machine Learning	Support Vector Machines (SVMs)	• Because SVMs can manage non-linear connections between variables, they are well-suited for complicated datasets. SVMs, unlike other methods like DT, are less prone to overfitting. Because SVMs are computationally efficient, they are well suited for current forecasting applications.	• Sensitivity to parameter selection • Limited interpretability • Limited handling of missing data • Limited handling of non-linear relationships • Limited scalability	[35]
	Decision trees (DTs)	• DTs are fast and efficient and are well suited for real-time rainfall forecasting scenarios that need processing missing data, non-parametric, speed, and effectiveness.	• Overfitting • Instability • Biases	[39]
	Random Forest (RF)	• RF can handle non-linear relationships, easily handle missing data, and generate importance rankings and robustness to overfitting.	• Lack of interpretability • Limited handling of multiple outputs and scalability	[44]
	Artificial Neural Networks (ANNs)	• ANNs can understand non-linear relationships, handling missing data, generalization, and adaptability.	• Overfitting • Computational complexity and Interpretability	[48]
	K-Nearest Neighbors (KNNs)	• KNNs are useful because of their simplicity, non-parametric, and adaptability, and KNNs need no training.	• Choice of k • Computationally intensive • Sensitivity to outliers	[52]
	Bayesian Method	• The Bayesian method can handle small data sets, model selection and evaluation, and uncertainty quantification.	• Computational complexity • Choice of the past distribution • Model complexity	[56]
Deep Learning	Convolutional Neural Networks (CNNs)	• CNN can improve the accuracy of rainfall forecasts, handle complex data, and understand relationships.	• Requires a large amount of data to learn features effectively. • It is a black-box model, which means that it is difficult to interpret the internal workings of the model.	[61]
	Feed-forward Neural Networks (FFNNs)	• FFNN can capture complex relationships. It also can handle big data with more accuracy for forecasting.	• Overfitting occurs when the model is too complex, and the internal mechanisms of the model are difficult to interpret.	[66]

Table 2. *Cont.*

	AITs	Advantages	Disadvantages	Reference
Deep Learning	Recurrent Neural Networks (RNNs)	• RNN can handle sequential data and detect temporal dependencies in the data. This is especially important for activities like rainfall forecasting because the present prediction is based on earlier measurements. • RNNs can handle variable-length sequences, which is essential for dealing with rainfall data that may have missing values or erratic time intervals. Another advantage of RNNs is their capacity to handle complex non-linear data interactions.	• Suffer from vanishing or exploding gradients during training and computationally expensive.	[67]
	Deep Neural Networks (DNNs)	• DNNs can learn hierarchical representations of data, handle complex data, and understand relationships.	• DNNs are computationally costly and susceptible to overfitting, especially with small datasets.	[70]
	Wavelet Neural Networks (WNNs)	• WNNs can also manage enormous datasets, making them well-suited for jobs like rainfall forecasting, which may involve many meteorological variables.WNNs also have the potential to learn complex non-linear correlations in data. It is critical for rainfall forecasting, where the correlations between meteorological factors and rainfall can be highly non-linear.	• WNNs are vulnerable to overfitting, however, approaches such as dropout and normalization have been developed to mitigate this issue, while it can still be an issue in some circumstances.	[73,77]

5. Overview of Artificial Intelligence Techniques in Thailand

In Thailand, several rainfall forecasting methods, including NWP, Statistical, AITs, and Hybrid methods, include using statistical methods to calibrate NWP forecasts or ensemble forecasts to inform ML models. It can be seen in Table 3, the methods used in Thailand for rainfall forecasting are constantly evolving and improving as new techniques and technologies become available. Table 3 provides a detailed overview of AITs application in rainfall forecasting over Thailand.

Overall, AITs have shown promising results for rainfall forecasting in Thailand. Their use will likely continue due to their ability to handle complex relationships between variables and their flexibility in modeling various time scales and regions. In this section, a comprehensive overview of different ATIs that have been applied in different regions of Thailand is given.

Jareanpon et al. (2004) developed a novel approach utilizing an Adaptive RBFNN to predict rainfall patterns one year in advance. The methodology involves the implementation of a genetic algorithm to establish the most practical value for the width, also known as the spread factor, of the hidden units. The network's iterative growth involves adding a single hidden node during each training epoch until the network achieves its optimal performance. The optimal number of concealed neurons is automatically ascertained. The test outcomes suggest slight variations between the anticipated and actual rainfall measurements. Hence, using a genetic algorithm to optimize the adaptive RBFNN is a highly effective model for forecasting rainfall [78].

Hung et al. (2008) developed an ANN model to enhance the accuracy of rainfall predictions. This empirical investigation was conducted in Bangkok. The research employed a four-year dataset and comprised hourly readings obtained from 75 regional rain gauge stations. The objective was to develop an AANN model. The devised ANN model is currently being employed for real-time rainfall forecasting and flood management in Bangkok, Thailand. Various network types were evaluated using diverse input data to generate forecasts in an almost real-time schedule. The findings indicate that implementing a generalized FFNN model utilizing a hyperbolic tangent transfer function yielded optimal results regarding the generalization of rainfall based on preliminary testing. The findings suggest that ANN predictions exhibit a higher level of effectiveness when compared to those generated by the persistent model. The accuracy of the rainfall predictions for Bangkok within 1 to 3 h was significantly high. The findings of the sensitivity analysis suggest that, in addition to rainfall, the wet bulb temperature is a crucial input parameter for accurately predicting rainfall [79].

Ingsrisawang et al. (2008) employed ML techniques to develop a short-term rain forecasting system. The current research utilized DT, ANN, and SVM algorithms to develop DT models with the objective of forecasting rainfall in the northeastern area of Thailand. Using the five-fold cross-validation technique, the classification tree demonstrates a general accuracy of 94.41%. The C4.5 algorithm was utilized to classify the level of rainfall into three discrete categories: absence of rainfall (0–0.1 mm), low rainfall (0.1–10 mm), and moderate rainfall (>10 mm). The accuracy of the classification tree was determined to be 62.57% in total. The study employed an ANN to predict the rainfall amounts. The RMSE values were analyzed, and the results indicated that the ANN accurately predicted the daily rainfall with an RMSE of 0.171. This performance was compared to the accuracy of the predictions made for the next day and the following two days. The ANN and SVM models demonstrated an overall accuracy of 68.15% and 69.10%, respectively, in predicting the outcomes on the same day. The results compare the predictive capabilities of various methods for estimating rainfall [80].

Phusakulkajorn et al. (2009) introduced a novel approach for rainfall prediction utilizing a hybrid model that combines ANNs and wavelet decomposition. The model has been developed to acquire knowledge and predict sequential daily rainfall trends considering antecedent rainfall data. Two distinct sets of wavelet coefficients are computed for the ANNs. One set is designed to capture the intricate details of the rainfall data, while the other is intended to function as a filter for smoothing. An NN utilizing the back-propagation algorithm is utilized in the learning and knowledge extraction processes. Based on historical data from the TMD and Royal Irrigation Department, it has been determined that the above-mentioned study's are susceptible to significant rainfall patterns and subsequent flood events. The network under consideration can predict daily rainfall up to four days ahead, with a precision of R^2 = 0.8819 and an RMSE value of 4.6912 mm [81].

Sopipan (2014) investigated the rainfall patterns in the Nakhon Ratchasima province, Thailand, by analyzing a time series dataset collected from weather stations. The utilization of time-series analysis is an effective technique in the modeling and prediction of rainfall patterns. The ARIMA and Holt-Winter models were constructed based on the principles of exponentially smoothed models. All the models showed satisfactory adequacy. Hence, it is possible to furnish information that can assist policymakers in devising strategies for properly administrating farming, irrigation networks, and other water-centric utilities in the region of Nakhon Ratchasima. The ARIMA model with parameters (1,0,1)(1,0,1)12 demonstrated the best forecasting performance [82].

Lueangaram and Waraporn (2016) compared Back Propagation NN and Time-Lagged Back Propagation NN with gamma memory. The research encompassed the creation of four different models to analyze the Yom and Nan Rivers in Thailand. The results suggest that the non-linear nature of the river flow can be attributed to its ongoing fluctuations. Implementing the Time-Lagged Back Propagation NN has been observed to improve the prognostic precision of the Back Propagation Neural Network in the domain

of flood prediction. Thus, the results suggest that the Time-Lagged Back Propagation NN performs better than the other models in the winter season. More training and testing data is necessary to evaluate the optimal dataset size, necessitating additional effort. Moreover, optimizing the number of layers and nodes could potentially enhance the results [83].

Weesakul et al. (2018) explored the potential of a DNN in forecasting the monthly rainfall in the eastern region of Thailand to analyze the impact of various atmospheric layers. The training process of the DNN model employed the monthly rainfall data obtained from the Pluak Deang station spanning the years 1991 to 2010. The model's validation was carried out using monthly rainfall data encompassing 2011 and 2016. The study's results suggest that the Deep Neural Network (DNN) can predict the monthly rainfall with a lead time of one to twelve months. Nevertheless, it has been observed that the precision of the forecast diminishes with an increase in the forecast time horizon. The most practical forecasting horizon is one month, covering around 70% of the predicted values within one standard deviation from the observed values [84].

Mahat et al. (2020) developed a model, namely the monthly rainfall deep neural network (MRDNN), in the eastern region of Thailand for monthly rainfall forecasting. The objective of this research was to enhance the precision of the forecast of the model by employing a DNN in conjunction with the method of selecting the most predictive variables. The DNN model was trained using monthly rainfall data from the Pluak Daeng station from 1991 to 2010. Subsequently, time series data from 2011 to 2016 were utilized to validate the model. The utilization of stochastic efficiency was employed as a criterion for the assessment of the precision of the forecast. The study employed an input selection technique to reduce the number of large-scale atmospheric variables (LAV) used as predictors in the model from 32 to 8 variables. These variables include air temperature, sea surface temperature, precipitable water, specific humidity, and outgoing longwave radiation. The results indicate that this approach leads to a higher level of forecast accuracy, with a stochastic efficiency of 72% for a one-month lead time. The DNN monthly rainfall forecast model has demonstrated satisfactory accuracy, with a forecast precision of approximately 70% for a forecast horizon of up to three months. The study aimed to investigate additional enhancements to the model to achieve greater accuracy in forecasting over an extended period [85].

Srithagon et al. (2021) investigated the effectiveness of solely utilizing rain gauge data for prediction in Bangkok, Thailand. This study examined four distinct types of learning machines, namely classification and regression tree (CART), MLP, RF, and SVM. The findings indicated that the practice of nowcasting is a viable option. Based on the results of the experiments, it was found that the F1 performance at the crucial 90-min lead time, which plays a pivotal role in determining future activities, was observed to be average for CART, MLP, RF, and SVM, with values of 0.69, 0.59, 0.73, and 0.63, respectively [86].

Limsakul (2021) states that the daily rainfall intensity in Thailand from 1955 to 2019 has substantially altered the lower and upper distribution tails. It has brought a significant reduction in light rainfall events and a significant rise in heavy rainfall events. The predominant trends in all ten rainfall categories for the wet-season, dry-season, and annual periods indicate that most regions in Thailand have observed a rise in the proportion of heavy rainfall occurrences. The study's findings provide scientific evidence to endorse efficient water management in the agricultural domain and to cope with the consequences of climate-induced extremes and calamities [87].

Manokij et al. (2021) introduced a DL framework to predict rainfall patterns in Thailand. They proposed two cascading models; first, a CNN is employed to categorize instances as rain or non-rain while simultaneously tackling the issue of an overabundance of non-rain cases through focal loss. The second point pertains to the utilization of a gated recurrent unit (GRU) in rainfall regression. The study was carried out on the rainfall dataset in Thailand, spanning from 2012 to 2018. The findings indicate that implementing focal

loss leads to enhanced classification accuracy across all regions, thereby contributing to an increase in the rate of rainfall detection. The southern region exhibited a significant 59.02% enhancement in the F1 score. Furthermore, the team has enhanced the accuracy of rainfall forecasting by incorporating autoencoder loss. The proposed model demonstrated superior accuracy in predicting rainfall levels across all regions, particularly in the eastern region, where it achieved a reduction of 1.50% in RMSE [88].

Sudprasert and Supratid (2022) suggested the diverse adaptations of conditional decoder variational autoencoder, utilizing convolutional gated recurrent unit (ConvGRU) architecture, specifically conditional-decoder variational autoencoders (CD-VAEs), for spatial-temporal rainfall nowcasting in Thailand. This study employed a multi-channel approach to integrate eight rainfall-related variables from the fifth-generation ECMWF Re-Analysis (ERA5) into the models. The input and output hourly time steps are set at four each. Various variables associated with rainfall are integrated as multi-channel inputs for the models. The three CDVAE models—conditional variational autoencoder with ordinary features (Cond-O), conditional variational autoencoder with Hierarchical features (Cond-H), and conditional variational autoencoder with latent space features (Cond-Z)—exhibited variations in the transmission of hidden states, H, and latent representation, Z, from the encoder to the decoder. Performance evaluations in data analysis often utilize F1 scores, RMSE, and false negative (FN) metrics. This is because a significant portion of the data falls within the category of little to no rainfall, making it difficult to detect and accurately measure. The comparative findings reveal that CD-VAEs produce an averaged F1 score of at least 74.81%, superior to the unconditional model. Using a sole initial-state decoder by Cond-O, which receives Z as its input, yields superior nowcasting outcomes in terms of the mean values of RMAE, F1, and FN. The study reports the performance of Cond-O in predicting rainfall intensity within two ranges: 0–0.5 mm./hour and 5–72 mm./hour. The model yielded F1 and RMAE scores of 0.9467 and 0.0347, respectively, with an 83.69% frequency rate in the first range. In the second range, with a lower frequency rate of 0.35%, the model produced scores of 0.4244 and 0.6955. Upon visual analysis of the step-by-step output, it was observed that the decoding states at all time steps, specifically Cond-Z, resulted in the lowest rate of performance decrease over time [89].

Table 3. Overview of Artificial Intelligence Techniques in Thailand from 2004–2022.

AITs	Input Data	Duration of Data	Source of Data	Forecast Type	Territory	Evaluation Criteria	Effectiveness of Study	Reference
Adaptive RBFNN with genetic algorithm	Monthly Rainfall Dataset	14 Rainfall stations data for 30 years (1971–2000)	TMD	Monthly Rainfall Prediction	Thailand	Sum square error (SSE)	Genetic Algorithms to optimize the adaptive RBF NN represents a very good model for the prediction of rainfall.	[78]
ANN and SVM	Rainfall, wind, cloud cover, relative humidity, and Sunshine data	Daily Weather station dataset and GPCM + RADAR (2004–2006)	Chalermprakiat Royal Rain Making Research Center, TMD and GPCM + RADAR	Short-Term Rain Forecasting	Northeastern Part of Thailand	RMSE	The ANN and SVM models demonstrated an overall accuracy of 68.15% and 69.10%, respectively, in predicting outcomes on the same day.	[80].
ANNs combined with wavelet decomposition	Daily rainfall data	Rainfall data from the monitoring Stations (1995–2006)	TMD and Royal Irrigation Department	Daily Rainfall Prediction	Five provinces of Thailand	RMSE and R^2	The network under consideration can predict daily rainfall up to 4 days ahead, with a precision of R^2 = 0.8819 and an RMSE value of 4.6912 mm.	[81].
ARIMA and Holt-Winter models	Monthly rainfall data	Fifteen stations from April 2005 to March 2013.	Hydrology and Water Management Center for Lower Northeastern Region	Monthly Rainfall Forecasting	Nakhon Ratchasima Province, Thailand	Mean Absolute Percentage Error (MAPE), Mean Square Error (MSE), and Mean Absolute Error (MAE)	The ARIMA Model (1,0,1)(1,0,1)12 yielded the optimal forecasting performance	[82].
Back Propagation NN and Time-Lagged Back Propagation NN with gamma memory	Rainfall and flow dataset	Rainy and winter season daily dataset (2012–2015) and	Not Available	Forecasting of Rainfall for flood prediction	Yom and Nan Rivers in Thailand	RMSE, Coefficient of Correlation, R, and Coefficient of Determination	Time-Lagged Back Propagation NN performs better than the other models during the winter season	[83]
DNN based Models	Monthly rainfall Data and Large Atmospheric Variables (LAVs)	Rainfall station data and LAVs from 1991 to 2016	Pluak Deang station and Earth System Research Laboratory (ESRL)	Monthly rainfall forecasting	The eastern region of Thailand	Stochastic efficiency (%)	DNN can forecast monthly rainfall for a period ranging from one to twelve months in advance	[84]
DNN based model	Monthly rainfall data and LAVs	Rainfall station data and Large Atmospheric Variables from 1991 to 2016	TMD and Earth System Research Laboratory (ESRL)	Monthly Rainfall Forecasting	Khlong Yai river basin, Thailand	Stochastic efficiency (%)	The DNN monthly rainfall forecast model has demonstrated satisfactory accuracy, with a forecast precision of approximately 70% for a forecast horizon of up to three months.	[85].
Classification and Regression Tree (CART), MLP, RF, and SVM.	5-min time interval rain gauge dataset	90 min of rain gauge data from 130 stations	Department of Drainage and Sewage and Bangkok Metropolitan Administration	Forecasting of rainfall Nowcasting	Bangkok Metropolitan Area, Thailand	Recall, precision, and F1 score	F1 performance was average for CART, MLP, RF, and SVM, with values of 0.69, 0.59, 0.73, and 0.63, respectively.	[86].

Table 3. *Cont.*

AITs	Input Data	Duration of Data	Source of Data	Forecast Type	Territory	Evaluation Criteria	Effectiveness of Study	Reference
Mann-Kendall test and PCA	Daily rainfall data and Global Surface Temperature	Daily rainfall data (1955–2019) and Global Surface Temperature (1951–1980)	TMD and Goddard Institute for Space Studies (GISS) and Global Historical Climatology Network (GHCN), the Scientific Committee on Antarctic Research (SCAR), the Hadley Centre Global Sea Ice and Sea Surface Temperature (HadISST), and the Optimum Interpolation Sea Surface Temperature(OISST)	Changes in daily rainfall intensity	Thailand	N/A	The study's findings provide scientific evidence to endorse efficient water management in the agricultural domain and to cope with the consequences of climate-induced extremes and calamities.	[87]
CNNs, ConvLSTM, and ConvGRUs	ERA5 hourly data and Reanalysis of the global climate and weather observation data set from ECMWF	Hourly Dataset	ERA5 and ECMWF	Spatial-Temporal Rainfall Nowcasting	Thailand	Root mean squared errors (RMAEs), along with false negative (FN) and F1 score	Overall, all three models performed well in three different conditions.	[89]

6. Results and Discussion

The following are the responses to the RQs after conducting a comprehensive investigation and analyzing the articles selected for further consideration.

RQ-1: Which AITs have been used or proposed for rainfall forecasting?

All selected publications presented mining algorithms that were adapted, integrated, or otherwise altered to produce more accurate rainfall forecasts. In each study, multiple climatic characteristics and variables derived from previous climate data were used as indicators for the prediction process. The precision of rainfall forecasts was intended to be improved due to each study's efforts.

RQ-2: How is the effectiveness of forecast techniques evaluated?

In the selected studies, comparisons are made between the suggested method or model and one or more methods that have been published in the past. The performance was assessed by comparing the expected results and metrics and those obtained (observed). By applying data-gathering metrics, the efficiency of the planned retrieval techniques was compared to that of other methods discovered in the current body of research.

RQ-3: What type of dataset is used for forecasting?

Each chosen publication made rainfall forecasts using historical meteorological, Radar, or satellite data and utilized supervised data mining algorithms to educate individuals. In addition to the supervised approaches that were already in place, unsupervised AIT techniques were also applied. Numerous environmental indicators were used to predict the rainfall polarity, volume, lowest and highest temperature, wind speed, and humidity. In addition to wind speed and humidity, additional meteorological variables were considered. Researchers believe that the introduction of additional features does not guarantee a higher level of accuracy in prediction and that the addition of traits that are not necessary may hinder the performance. For accurate rainfall forecasting, a combination of essential characteristics is required, and the specifics of these combinations change depending on the situation. Therefore, before any modeling, we must design definite criteria for input selection for forecasting purposes.

RQ-4: For which study area is the rainfall forecast generated?

According to the considered publications, rainfall was predicted in different regions of the United States of America, Australia, Brazil, China, Indonesia, Iran, India, Malaysia, and Thailand.

RQ-5: Which variables influence the accuracy of predictions?

After conducting an in-depth analysis of the papers that were put forward for consideration in the competition, it was determined that the subsequent factors might potentially affect the results of the rainfall prediction: weather data, which is utilized for training the data mining technique; climatic attributes, which are used as predictors; the place for which rainfall forecasting be made; the environment that is immediately surrounding the location; pre-processing methods; and, of utmost significance, the rainfall prediction model itself.

RQ-6: What are the most recent study trends in the field of rainfall forecasting?

The enhancement of forecast accuracy was the goal of all the papers that made the shortlist. To achieve this, the researchers evaluated the relationship between meteorological characteristics and prediction and sought the optimal combinations of these characteristics to enhance the performance. On the other hand, only a few academics tried to train AITs to achieve high prediction accuracy properly in Thailand. Comparing contemporary strategies to more classic ones has not been conducted very often. However, most studies presented or utilized an integrated methodology and highlighted using two or more techniques for prediction. The authors hypothesized that their methods would, as a result, produce more reliable findings. In each investigation, the efficiency of the presented, intended, or applied method was evaluated using quality metrics that supported the technique.

7. Conclusions

The literature mentioned herein discussed supervised ML, ANN, and DL AITs. The applications of these techniques were studied in different countries around the globe

(second section of the review), and all the authors highlighted some important benefits and drawbacks. Following the analysis of all the techniques and their basic working principles, this review concluded some weaknesses and strengths of these AITs. The last section explored all of the applied ML, ANNs, and DL techniques in different regions of Thailand. In these studies, the basic architecture of all these AITs were employed, as well as some hybrid models, such as CNNs, ConvLSTM, ConvGRUs, DNN hybrid models, Adaptive RBFNN with a genetic algorithm, and ANNs with two variations of Wavelet transformation. Based on the current literature and to the best of the authors' knowledge, there is a huge gap where AITs can play a crucial role in managing data, input selections, and developing advanced models for rainfall forecasting in different regions and provinces of Thailand because there are no such studies available where the whole country is studied as a study area using the advancements of Artificial Intelligence. Using AITs to improve rainfall forecasting in Thailand is a promising development. Applying ML algorithms and ANNs to analyze historical and real-time data can help forecasters create predictive models to forecast rainfall accurately. We can improve this efficiency through combining different AITs (bootstrapping, Wavelet transformation with ML, ANN, and DL techniques). This can significantly improve the accuracy of rainfall forecasting and provide timely warnings in cases of severe weather events.

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Abbreviations

AITs	Artificial Intelligence Techniques
AI	Artificial Intelligence
ML	Machine Learning
ANNs	Artificial Neural Networks
DL	Deep Learning
RQs	Research Questions
ICs	Inclusion Conditions
ECs	Exclusion Conditions
SVM	Support Vector Machine
FL	Fuzzy Logic
DT	Decision Trees
RFs	Random Forests
KNN	K-Nearest Neighbors
FFNN	Feed-Forward Neural Networks
WNNs	Wavelet Neural Networks

DNNs	Deep Neural Networks
CNNs	Convolutional Neural Networks
RNNs	Recurrent Neural Networks
SVD,	Singular Value Decomposition
PCA	Principal Component Analysis
ICA	Independent Component Analysis
SVR	Support Vector Regression
MKSVR-SARIMA	Multi-Kernel SVR Seasonal Autoregressive Integrated Moving Average
SVM-FA	SVM With A Firefly Algorithm
RMSE	Root Means Square Error
NSE	Nash-Sutcliffe Efficiency
SMO	Sequential Minimal Optimization
RC	Random Committee
DA	Dagging
AR	Additive Regression
LDA	Linear Discriminant Analysis
LS-SVR	Least Square Support Vector Regression
ROC	Receiver Operating Characteristic Curve
RF	Radiofrequency
MRA	Multiple Regression Analysis
APST	Approximation and Prediction of Stock Time-Series
BNN	Bayesian Neural Network
HBV	Hydrologiska Byråns Vattenbalansavdelning
HPD	Highest Posterior Density
MSE	Mean Squared Error
MLPNN	Multilayer Perceptron Neural Network
SCG	Sigmoid Transfer Function
MAE	Mean Absolute Error
LSTM	Long Short-Term Memory
CRNN	Convolutional Recurrent Neural Network
ARIMA	Autoregressive Integrated Moving Average
SNNs	Shallow Neural Networks
SE	Stochastic Efficiency
LAV	Large-Scale Atmospheric Variables
DWT	Discrete Wavelet Transform
FFBP	Feed Forward Back Propagation
NWP	Numerical Weather Prediction
RBFNN	Radial Basis Feed Forward Neural Network
TMD	Thai Metrological Department
MRDNN	Monthly Rainfall Deep Neural Network
CART	Classification and Regression Tree
GRU	Gated Recurrent Unit
CD-VAEs	Conditional-Decoder Variational Autoencoders
ECMWF	European Centre for Medium-Range Weather Forecasts
Cond-O	Conditional Variational Autoencoder with Ordinary Features
Cond-H	Variational Autoencoder with Hierarchical Features
Cond-Z	Conditional Variational Autoencoder with Latent Space Features
SSE	Sum Square Error
MAPE	Mean Absolute Percentage Error
MAE	Mean Absolute Error
GPCM	General Purpose Chip Select Machine
GISS	Goddard Institute for Space Studies
GHCN	Global Historical Climatology Network
SCAR	Scientific Committee on Antarctic Research
HadISST	Hadley Centre Global Sea Ice and Sea Surface Temperature
OISST	Optimum Interpolation Sea Surface Temperature
ECMWF	European Centre for Medium-Range Weather Forecasts
R^2	Coefficient of Determination

References

1. Parmar, A.; Mistree, K.; Sompura, M. Machine learning techniques for rainfall prediction: A review. In Proceedings of the International Conference on Innovations in information Embedded and Communication Systems, Coimbatore, India, 17–18 March 2017.
2. Davolio, S.; Miglietta, M.; Diomede, T.; Marsigli, C.; Morgillo, A.; Moscatello, A.J.N.H.; Sciences, E.S. A meteo-hydrological prediction system based on a multi-model approach for precipitation forecasting. *Nat. Hazards Earth Syst. Sci.* **2008**, *8*, 143–159. [CrossRef]
3. Zaw, W.T.; Naing, T.T. Empirical statistical modeling of rainfall prediction over Myanmar. *World Acad. Sci. Eng. Technol.* **2008**, *2*, 500–504.
4. Poornima, S.; Pushpalatha, M. Prediction of rainfall using intensified LSTM based recurrent neural network with weighted linear units. *Atmosphere* **2019**, *10*, 668. [CrossRef]
5. Adaryani, F.R.; Mousavi, S.J.; Jafari, F. Short-term rainfall forecasting using machine learning-based approaches of PSO-SVR, LSTM and CNN. *J. Hydrol.* **2022**, *614*, 128463. [CrossRef]
6. Ridwan, W.M.; Sapitang, M.; Aziz, A.; Kushiar, K.F.; Ahmed, A.N.; El-Shafie, A. Rainfall forecasting model using machine learning methods: Case study Terengganu, Malaysia. *Ain Shams Eng. J.* **2021**, *12*, 1651–1663. [CrossRef]
7. Liu, Z.; Han, X.-H. Deep self-supervised hyperspectral image reconstruction. *ACM Trans. Multimed. Comput. Commun. Appl. (TOMM)* **2022**, *18*, 1–20. [CrossRef]
8. Aftab, S.; Ahmad, M.; Hameed, N.; Bashir, M.S.; Ali, I.; Nawaz, Z. Rainfall prediction using data mining techniques: A systematic literature review. *Int. J. Adv. Comput. Sci. Appl.* **2018**, *9*, 143–150. [CrossRef]
9. Aftab, S.; Ahmad, M.; Hameed, N.; Bashir, M.S.; Ali, I.; Nawaz, Z. Rainfall prediction in Lahore City using data mining techniques. *Int. J. Adv. Comput. Sci. Appl.* **2018**, *9*, 254–260. [CrossRef]
10. Yadav, A.K.; Chandola, V.K.; Singh, A.; Singh, B.P. Rainfall-runoff modelling using artificial neural networks (ANNs) model. *Int. J. Curr. Microbiol. Appl. Sci.* **2020**, *9*, 127–135. [CrossRef]
11. Abbot, J.; Marohasy, J. Forecasting of medium-term rainfall using Artificial Neural Networks: Case studies from Eastern Australia. *Eng. Math. Top. Rainfall* **2018**, *33*. [CrossRef]
12. Janarthanan, R.; Balamurali, R.; Annapoorani, A.; Vimala, V. Prediction of rainfall using fuzzy logic. *Mater. Today Proc.* **2021**, *37*, 959–963. [CrossRef]
13. French, M.N.; Krajewski, W.F.; Cuykendall, R.R. Rainfall forecasting in space and time using a neural network. *J. Hydrol.* **1992**, *137*, 1–31. [CrossRef]
14. Shrivastava, G.; Karmakar, S.; Kowar, M.K.; Guhathakurta, P. Application of artificial neural networks in weather forecasting: A comprehensive literature review. *Int. J. Comput. Appl.* **2012**, *51*, 17–29.
15. Ayuba, P.; Abdullateef, M. Comparative analysis of the performance of artificial neural networks (ANNs) and autoregressive integrated moving average (ARIMA) models on rainfall forecasting. *Sci. World J.* **2018**, *13*, 100–105.
16. Esteves, J.T.; de Souza Rolim, G.; Ferraudo, A.S. Rainfall prediction methodology with binary multilayer perceptron neural networks. *Clim. Dyn.* **2019**, *52*, 2319–2331. [CrossRef]
17. Chokngamwong, R.; Chiu, L. TRMM and Thailand daily gauge rainfall comparison. In Proceedings of the Reprints, 20th Conference on Hydrology, Atlanta, GA, USA, 27 January 2006.
18. Sangkhaphan, S.; Shu, Y. Impact of rainfall on agricultural growth in Thailand: Evidence in farming and fishing activities. *J. Econ. Sustain. Dev.* **2019**, *10*, 162–174.
19. Mengist, W.; Soromessa, T.; Legese, G. Method for conducting systematic literature review and meta-analysis for environmental science research. *MethodsX* **2020**, *7*, 100777. [CrossRef]
20. Ashok, S.P.; Pekkat, S. A systematic quantitative review on the performance of some of the recent short-term rainfall forecasting techniques. *J. Water Clim. Chang.* **2022**, *13*, 3004–3029. [CrossRef]
21. Bewoor, L.A.; Bewoor, A.; Kumar, R. Artificial intelligence for weather forecasting. In *Artificial Intelligence*; CRC Press: Boca Raton, FL, USA, 2021; pp. 231–239.
22. Al-Qammaz, A.; Darabkh, K.A.; Abualigah, L.; Khasawneh, A.M.; Zinonos, Z. An ai based irrigation and weather forecasting system utilizing lorawan and cloud computing technologies. In Proceedings of the 2021 IEEE Conference of Russian Young Researchers in Electrical and Electronic Engineering (ElConRus), St. Petersburg, Russia, 26–29 January 2021; pp. 443–448.
23. Hernández, E.; Sanchez-Anguix, V.; Julian, V.; Palanca, J.; Duque, N. Rainfall prediction: A deep learning approach. In Proceedings of the Hybrid Artificial Intelligent Systems: 11th International Conference, HAIS 2016, Seville, Spain, 18–20 April 2016; pp. 151–162.
24. Waqas, M.; Shoaib, M.; Saifullah, M.; Naseem, A.; Hashim, S.; Ehsan, F.; Ali, I.; Khan, A. Assessment of advanced artificial intelligence techniques for streamflow forecasting in Jhelum River Basin. *Pak. J. Agric. Res.* **2021**, *34*, 580. [CrossRef]
25. Waqas, M.; Bonnet, S.; Wannasing, U.H.; Hlaing, P.T.; Lin, H.A.; Hashim, S. Assessment of Advanced Artificial Intelligence Techniques for Flood Forecasting. In Proceedings of the 2023 International Multi-disciplinary Conference in Emerging Research Trends (IMCERT), Karachi, Pakistan, 4–5 January 2023; pp. 1–6.
26. Kunjumon, C.; Nair, S.S.; Suresh, P.; Preetha, S. Survey on weather forecasting using data mining. In Proceedings of the 2018 Conference on Emerging Devices and Smart Systems (ICEDSS), Tamilnadu, India, 2–3 March 2018; pp. 262–264.

27. Weesakul, U.; Chaiyasarn, K.; Mahat, S. Long-term rainfall forecasting using deep neural network coupling with input variables selection technique: A case study of Ping River Basin, Thailand. *Eng. Appl. Sci. Res.* **2021**, *48*, 209–220.
28. Yin, G.; Yoshikane, T.; Yamamoto, K.; Kubota, T.; Yoshimura, K. A support vector machine-based method for improving real-time hourly precipitation forecast in Japan. *J. Hydrol.* **2022**, *612*, 128125. [CrossRef]
29. Vapnik, V. *The Nature of Statistical Learning Theory*; Springer Science & Business Media: Berlin/Heidelberg, Germany, 1999.
30. Vafakhah, M.; Khosrobeigi Bozchaloei, S. Regional analysis of flow duration curves through support vector regression. *Water Resour. Manag.* **2020**, *34*, 283–294. [CrossRef]
31. Gönen, M.; Alpaydın, E. Multiple kernel learning algorithms. *J. Mach. Learn. Res.* **2011**, *12*, 2211–2268.
32. Caraka, R.E.; Bakar, S.A.; Tahmid, M. Rainfall forecasting multi kernel support vector regression seasonal autoregressive integrated moving average (MKSVR-SARIMA). *AIP Conf. Proc.* **2019**, *2111*, 020014.
33. Chao, C.-F.; Horng, M.-H. The construction of support vector machine classifier using the firefly algorithm. *Comput. Intell. Neurosci.* **2015**, *2015*, 212719. [CrossRef]
34. Danandeh Mehr, A.; Nourani, V.; Karimi Khosrowshahi, V.; Ghorbani, M.A. A hybrid support vector regression–firefly model for monthly rainfall forecasting. *Int. J. Environ. Sci. Technol.* **2019**, *16*, 335–346. [CrossRef]
35. Karamizadeh, S.; Abdullah, S.M.; Halimi, M.; Shayan, J.; Javad Rajabi, M. Advantage and drawback of support vector machine functionality. In Proceedings of the 2014 International Conference on Computer, Communications, and Control Technology (I4CT), Langkawi, Malaysia, 2–4 September 2014; pp. 63–65.
36. Humphries, U.W.; Ali, R.; Waqas, M.; Shoaib, M.; Varnakovida, P.; Faheem, M.; Hlaing, P.T.; Lin, H.A.; Ahmad, S. Runoff Estimation Using Advanced Soft Computing Techniques: A Case Study of Mangla Watershed Pakistan. *Water* **2022**, *14*, 3286. [CrossRef]
37. Dou, J.; Yunus, A.P.; Bui, D.T.; Merghadi, A.; Sahana, M.; Zhu, Z.; Chen, C.-W.; Khosravi, K.; Yang, Y.; Pham, B.T. Assessment of advanced random forest and decision tree algorithms for modeling rainfall-induced landslide susceptibility in the Izu-Oshima Volcanic Island, Japan. *Sci. Total Environ.* **2019**, *662*, 332–346. [CrossRef]
38. Ahmadi, H.; Aminnejad, B.; Sabatsany, H. Application of machine learning ensemble models for rainfall prediction. *Acta Geophys.* **2022**, *71*, 1775–1786. [CrossRef]
39. Gulati, P.; Sharma, A.; Gupta, M. Theoretical study of decision tree algorithms to identify pivotal factors for performance improvement: A review. *Int. J. Comput. Appl.* **2016**, *141*, 19–25.
40. Zainudin, S.; Jasim, D.S.; Bakar, A.A. Comparative analysis of data mining techniques for Malaysian rainfall prediction. *Int. J. Adv. Sci. Eng. Inf. Technol.* **2016**, *6*, 1148–1153. [CrossRef]
41. Breiman, L. Random forests. *Mach. Learn.* **2001**, *45*, 5–32. [CrossRef]
42. Pham, Q.B.; Yang, T.-C.; Kuo, C.-M.; Tseng, H.-W.; Yu, P.-S. Combing random forest and least square support vector regression for improving extreme rainfall downscaling. *Water* **2019**, *11*, 451. [CrossRef]
43. Primajaya, A.; Sari, B.N. Random forest algorithm for prediction of precipitation. *Indones. J. Artif. Intell. Data Min.* **2018**, *1*, 27–31. [CrossRef]
44. Statnikov, A.; Wang, L.; Aliferis, C.F. A comprehensive comparison of random forests and support vector machines for microarray-based cancer classification. *BMC Bioinform.* **2008**, *9*, 1–10. [CrossRef]
45. Cai, B.; Yu, Y. Flood forecasting in urban reservoir using hybrid recurrent neural network. *Urban Clim.* **2022**, *42*, 101086. [CrossRef]
46. Hsieh, P.-C.; Tong, W.-A.; Wang, Y.-C. A hybrid approach of artificial neural network and multiple regression to forecast typhoon rainfall and groundwater-level change. *Hydrol. Sci. J.* **2019**, *64*, 1793–1802. [CrossRef]
47. Hossain, I.; Rasel, H.; Imteaz, M.A.; Mekanik, F. Long-term seasonal rainfall forecasting using linear and non-linear modelling approaches: A case study for Western Australia. *Meteorol. Atmos. Phys.* **2020**, *132*, 131–141.
48. ASCE Task Committee on Application of Artificial Neural Networks in Hydrology. Artificial neural networks in hydrology. I: Preliminary concepts. *J. Hydrol. Eng.* **2000**, *5*, 115–123. [CrossRef]
49. Ghorpade, P.; Gadge, A.; Lende, A.; Chordiya, H.; Gosavi, G.; Mishra, A.; Hooli, B.; Ingle, Y.S.; Shaikh, N. Flood Forecasting Using Machine Learning: A Review. In Proceedings of the 2021 8th International Conference on Smart Computing and Communications (ICSCC), Kochi, India, 1–3 July 2021; pp. 32–36.
50. Wu, C.; Chau, K.W.; Fan, C. Prediction of rainfall time series using modular artificial neural networks coupled with data-preprocessing techniques. *J. Hydrol.* **2010**, *389*, 146–167. [CrossRef]
51. Sharma, A.; Bose, M. Rainfall prediction using k-NN based similarity measure. In Proceedings of the Recent Advances in Information Technology: RAIT-2014 Proceedings, Dhanbad, India, 13–15 March 2014; pp. 125–132.
52. Papanikolaou, M.; Evangelidis, G.; Ougiaroglou, S. Dynamic k determination in k-NN classifier: A literature review. In Proceedings of the 2021 12th International Conference on Information, Intelligence, Systems & Applications (IISA), Chania Crete, Greece, 12–14 July 2021; pp. 1–8.
53. Nikam, V.B.; Meshram, B. Modeling rainfall prediction using data mining method: A Bayesian approach. In Proceedings of the 2013 Fifth International Conference on Computational Intelligence, Modelling and Simulation, Seoul, Republic of Korea, 24–25 September 2013; pp. 132–136.
54. Khan, M.S.; Coulibaly, P. Bayesian neural network for rainfall-runoff modeling. *Water Resour. Res.* **2006**, *42*. [CrossRef]
55. Kaewprasert, T.; Niwitpong, S.-A.; Niwitpong, S. Bayesian estimation for the mean of delta-gamma distributions with application to rainfall data in Thailand. *PeerJ* **2022**, *10*, e13465. [PubMed]

56. Norton, J.D. Challenges to Bayesian confirmation theory. In *Philosophy of Statistics*; Elsevier: Amsterdam, The Netherlands, 2011; pp. 391–439.
57. Kareem, S.; Hamad, Z.J.; Askar, S. An evaluation of CNN and ANN in prediction weather forecasting: A review. *Sustain. Eng. Innov.* **2021**, *3*, 148.
58. Narejo, S.; Jawaid, M.M.; Talpur, S.; Baloch, R.; Pasero, E.G.A. Multi-step rainfall forecasting using deep learning approach. *PeerJ Comput. Sci.* **2021**, *7*, e514.
59. Elhoseiny, M.; Huang, S.; Elgammal, A. Weather classification with deep convolutional neural networks. In Proceedings of the 2015 IEEE International Conference on Image Processing (ICIP), Quebec City, QC, Canada, 27–30 September 2015; pp. 3349–3353.
60. Liu, Y.; Racah, E.; Correa, J.; Khosrowshahi, A.; Lavers, D.; Kunkel, K.; Wehner, M.; Collins, W. Application of deep convolutional neural networks for detecting extreme weather in climate datasets. *arXiv* **2016**, arXiv:1605.01156.
61. Scher, S.; Messori, G. Predicting weather forecast uncertainty with machine learning. *Q. J. R. Meteorol. Soc.* **2018**, *144*, 2830–2841.
62. Singhroul, A.; Agrawal, S. Artificial Neural Networks in Weather Forecasting-A Review. In Proceedings of the 2021 International Conference on Advances in Technology, Management & Education (ICATME), Bhopal, India, 8–9 January 2021; pp. 9–14.
63. El-Shafie, A.; Noureldin, A.; Taha, M.; Hussain, A.; Mukhlisin, M. Dynamic versus static neural network model for rainfall forecasting at Klang River Basin, Malaysia. *Hydrol. Earth Syst. Sci.* **2012**, *16*, 1151–1169.
64. Paras, S.M.; Kumar, A.; Chandra, M. A feature based neural network model for weather forecasting. *Int. J. Comput. Intell.* **2009**, *4*, 209–216.
65. Velasco, L.C.P.; Serquiña, R.P.; Zamad, M.S.A.A.; Juanico, B.F.; Lomocso, J.C. Week-ahead rainfall forecasting using multilayer perceptron neural network. *Procedia Comput. Sci.* **2019**, *161*, 386–397.
66. Farizawani, A.; Puteh, M.; Marina, Y.; Rivaie, A. A review of artificial neural network learning rule based on multiple variant of conjugate gradient approaches. *J. Phys. Conf. Ser.* **2020**, *1529*, 022040.
67. Srinu, N.; Bindu, B.H. A Review on Machine Learning and Deep Learning based Rainfall Prediction Methods. In Proceedings of the 2022 International Conference on Power, Energy, Control and Transmission Systems (ICPECTS), Chennai, India, 8–9 December 2022; pp. 1–4.
68. Tran, T.T.K.; Bateni, S.M.; Ki, S.J.; Vosoughifar, H. A review of neural networks for air temperature forecasting. *Water* **2021**, *13*, 1294.
69. Dong, Y.; Wang, J.; Xiao, L.; Fu, T. Short-term wind speed time series forecasting based on a hybrid method with multiple objective optimization for non-convex target. *Energy* **2021**, *215*, 119180.
70. Dhar, D.; Bagchi, S.; Kayal, C.K.; Mukherjee, S.; Chatterjee, S. Quantitative rainfall prediction: Deep neural network-based approach. In *Proceedings of International Ethical Hacking Conference 2018*; Springer: Singapore, 2018; pp. 455–463.
71. Barman, U.; Sahu, D.; Barman, G.G. Comparison of LR, SVR, and DNN for the Rainfall Forecast of Guwahati, Assam. In Proceedings of the International Conference on Computing and Communication Systems; Springer: Singapore, 2021; pp. 297–304.
72. Zhang, J.; Walter, G.G.; Miao, Y.; Lee, W.N.W. Wavelet neural networks for function learning. *IEEE Trans. Signal Process.* **1995**, *43*, 1485–1497.
73. Estévez, J.; Bellido-Jiménez, J.A.; Liu, X.; García-Marín, A.P. Monthly precipitation forecasts using wavelet neural networks models in a semiarid environment. *Water* **2020**, *12*, 1909.
74. Wang, D.; Luo, H.; Grunder, O.; Lin, Y. Multi-step ahead wind speed forecasting using an improved wavelet neural network combining variational mode decomposition and phase space reconstruction. *Renew. Energy* **2017**, *113*, 1345–1358.
75. Venkata Ramana, R.; Krishna, B.; Kumar, S.; Pandey, N. Monthly rainfall prediction using wavelet neural network analysis. *Water Resour. Manag.* **2013**, *27*, 3697–3711.
76. Partal, T.; Cigizoglu, H.K.; Kahya, E. Daily precipitation predictions using three different wavelet neural network algorithms by meteorological data. *Stoch. Environ. Res. Risk Assess.* **2015**, *29*, 1317–1329.
77. Thuillard, M. A review of wavelet networks, wavenets, fuzzy wavenets and their applications. *Adv. Comput. Intell. Learn.* **2002**, *18*, 43–60.
78. Jareanpon, C.; Pensuwon, W.; Frank, R.; Davey, N. An adaptive RBF network optimised using a genetic algorithm applied to rainfall forecasting. In Proceedings of the IEEE International Symposium on Communications and Information Technology, 2004. ISCIT 2004, Sapporo, Japan, 26–29 October 2004; pp. 1005–1010.
79. Hung, N.; Babel, M.; Weesakul, S.; Tripathi, N. An artificial neural network model for rainfall forecasting in Bangkok, Thailand. *Hydrol. Earth Syst. Sci. Discuss.* **2008**, *5*, 183–218.
80. Ingsrisawang, L.; Ingsriswang, S.; Somchit, S.; Aungsuratana, P.; Khantiyanan, W. Machine learning techniques for short-term rain forecasting system in the northeastern part of Thailand. *Int. J. Comput. Inf. Eng.* **2008**, *2*, 1422–1427.
81. Phusakulkajorn, W.; Lursinsap, C.; Asavanant, J. Wavelet-transform based artificial neural network for daily rainfall prediction in Southern Thailand. In Proceedings of the 2009 9th International Symposium on Communications and Information Technology, Incheon, Republic of Korea, 28–30 September 2009; pp. 432–437.
82. Sopipan, N. Forecasting rainfall in Thailand: A case study of Nakhon Ratchasima Province. *Int. J. Environ. Chem. Ecol. Geol. Geophys. Eng.* **2014**, *8*, 777–781.
83. Lueangaram, S.; Waraporn, N. Time Lagged Back Propagation Neural Network with Rainfall for Flood Forecasting. In Proceedings of the 2016 IEEE 20th Jubilee International Conference on Intelligent Engineering Systems (INES), Budapest, Hungary, 30 June–2 July 2016; pp. 63–68.

84. Weesakul, U.; Kaewprapha, P.; Boonyuen, K.; Mark, O. Deep learning neural network: A machine learning approach for monthly rainfall forecast, case study in eastern region of Thailand. *Eng. Appl. Sci. Res.* **2018**, *45*, 203–211.
85. Mahat, S.; Chaiyasarn, K.; Weesakul, U. Improving Monthly Rainfall Forecast Model by Input Selection Technique using Deep Neural Network. *Sci. Technol. Asia* **2020**, *25*, 30–44.
86. Srithagon, S.; Phisanbut, N.; Piamsa-nga, N.; Piamsa-nga, P. Rainfall nowcasting based on neighboring rain gauge stations using learning machines. In Proceedings of the 2021 25th International Computer Science and Engineering Conference (ICSEC), Chiang Rai, Thailand, 18–20 November 2021; pp. 33–38.
87. Limsakul, A. Changes of daily rainfall intensity in Thailand from 1955 to 2019. *Changes* **2021**, *6*, 18.
88. Manokij, F.; Vateekul, P.; Sarinnapakorn, K. Cascading Models of CNN and GRU with Autoencoder Loss for Precipitation Forecast in Thailand. *ECTI Trans. Comput. Inf. Technol. (ECTI-CIT)* **2021**, *15*, 333–346.
89. Sudprasert, C.; Supratid, S. Using Variants of Conditional-Decoder VAE for Spatial-Temporal Precipitation Nowcasting in Thailand. In Proceedings of the 2022 19th International Conference on Electrical Engineering/Electronics, Computer, Telecommunications and Information Technology (ECTI-CON), Huahin, Thailand, 24–27 May 2022; pp. 1–4.

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