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RESEARCH PAPER

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AN IN-DEPTH ANALYSIS OF ARTIFICIAL INTELLIGENCE APPROACHES FOR RAINFALL PREDICTION

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Abstract: Natural disasters and floods brought on by heavy rainfall pose serious threats to human health and lives every year on a global scale. The intricacy of meteorological data makes it difficult to provide accurate rainfall predictions, despite their critical importance in nations like India where agriculture is the primary occupation. Rainfall forecasting has recently benefited from Artificial Intelligence (AI) developments such as Deep Learning (DL) and Machine Learning (ML) techniques. This article provides a comprehensive survey of recent studies that use AI techniques for rainfall prediction, analyzing them based on the ML algorithms and DL methods used, organized by publication year. The findings show that DL approaches are more effective than traditional ML methods and shallow neural network models. This research is important as it has significant impacts on agriculture, disaster preparedness, and water resource management. Finally, it outlines future research directions for further advancements in rainfall prediction through AI methodologies.

Keywords: Agriculture, Rainfall prediction, Artificial intelligence, Machine learning, Deep learning, Meteorological data

I. INTRODUCTION

All forms of life, from humans to plants, need on rainfall to stay alive. A key component of many agricultural and livestock production systems, it is an essential natural resource. Nevertheless, changes in climate and increasing greenhouse gas emissions have made it challenging to obtain the necessary amount of rainfall for human needs and environmental sustainability [1]. Therefore, it is essential to study changing rainfall patterns and predict rain not only for human use but also for ecological purposes, such as forecasting natural disasters caused by heavy rains.

A. *Significance of Rainfall*

Precipitation occurs when the air becomes saturated with vapor and can no longer maintain the water vapor in gaseous form, causing it to pour. Rainfall is the liquid form of precipitation and refers to the amount of precipitation received in a specific region over a period. There are three main types of rainfall: Convectional, Orographic, and Frontal [2].

Convectional rainfall occurs in areas with high temperatures, especially during summer months. Orographic rainfall occurs at the foot and windward side of a mountain, with the Western Ghats and foothills of the Himalayas being prime examples. Frontal rainfall occurs when pressure differences create storms and cyclones, often affecting coastal regions. From December through February, there is winter, from March through May, there is the monsoon or rainy season, from June through September, and from October through November, there is post-monsoon or autumn, according to the Indian Meteorological Department (IMD) [3]. Beginning in late May or early June and often receding from North India in early October, the humid southwest summer monsoon dominates the monsoon season. In the months following the monsoon, the southern region of India experiences an increase in precipitation. The northeast monsoon is when Tamil Nadu gets the majority of its annual rainfall. The monsoon is crucial to the agriculture industry.

Accurate rainfall prediction is essential for a variety of sectors, including marine forecasting, tourism forecasting, thunderstorm forecasting, winter fog forecasting, air quality forecasting, early warning systems, pilgrimage forecasting, and highway forecasting, especially for the agricultural sector [4]. It is also crucial for flood warning systems, to predict the depth and distribution of rainfall by considering factors such as temperature, pressure, wind speed, and wind direction. Accurately predicting rainfall involves observing atmospheric conditions and the development of advanced models to simulate interactions between atmospheric conditions and cumulus clouds [5].

B. *Factors Influencing Rainfall*

Rainfall is influenced by a variety of factors, as shown in Fig. 1 [6], including atmospheric and environmental conditions.

Some of the main factors that influence rainfall include:

- Temperature: More moisture can be held by warm air than by cold air. Clouds and precipitation are the results of water vapor condensing into droplets as warm, humid air rises and cools.
- Humidity: There is a lot of water vapor in the air when the humidity is high. Precipitation is released when the air reaches a saturation point and becomes unable to retain any more moisture.
- Wind patterns: which include air mass motion and the presence of jet streams, are important components in the redistribution of moisture, cloud formation, and precipitation.
- Topography: Mountain ranges and valleys are two examples of how topography can affect precipitation. The leeward side of a mountain can experience a rain shadow effect when air on the windward side is forced to rise, chill, and release moisture as precipitation.
- Pressure systems: Atmospheric pressure systems, including low and high-pressure areas, influence the movement of air masses and the associated weather

patterns. Low-pressure systems are often associated with rising air and the potential for precipitation.

- Ocean currents: Sea surface temperatures and ocean currents can affect the moisture content in the air. Regions near warm ocean currents tend to experience higher evaporation rates and contribute to increased atmospheric moisture.
- Monsoons: Seasonal wind patterns, such as the monsoon, can bring about changes in weather conditions. Monsoons, for example, are characterized by seasonal reversal of winds, leading to wet and dry seasons in certain regions.

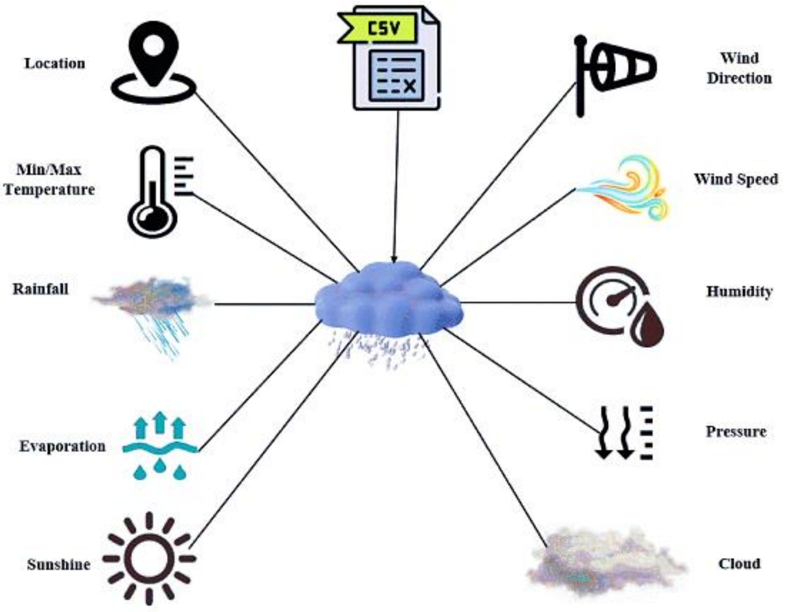

Figure 1. Factors Influencing Rainfall

- Solar radiation: Atmospheric circulation causes low- and high-pressure zones due to the sun's unequal heating of Earth's surface. This, in turn, affects how air masses move and how likely it is that it will rain.
- Cloud cover: The presence of clouds can either enhance or inhibit rainfall. Clouds reflect sunlight and contribute to cooling, but they can also trap heat and contribute to warming, affecting the atmospheric conditions for precipitation.
- Greenhouse gases: The concentration of greenhouse gases, such as carbon dioxide and water vapor, in the atmosphere can impact temperature and weather patterns, influencing the likelihood and intensity of rainfall events.

It is crucial to understand the complex interactions among these factors to predict regional and global rainfall patterns.

C. *Need for Rainfall Prediction*

Rainfall plays a significant role in human life. Predicting rainfall is a challenging natural phenomenon. It is the process of forecasting the amount and timing of precipitation, specifically rain, in a given geographical area over a defined period. It aims to provide information about when, where, and how much rain is likely to occur, helping individuals, communities, and organizations make informed decisions based on anticipated weather conditions. The accuracy and error in prediction, as well as the volume of rainfall, are important factors. Forecasters collect, analyze, verify, model, simulate, and research meteorological data and parameters [7]. Accurate rainfall information is essential for managing water resources, flood prevention, and reservoir operation. It also has a strong influence on urban sewer systems, traffic, and human activities. Rainfall occurs over a wide range of scales, making accurate prediction challenging in operational hydrology [8]. While traditional and statistical models are commonly used for forecasting, ML, and DL techniques have shown high accuracy and minimal error rates in the rainfall prediction process.

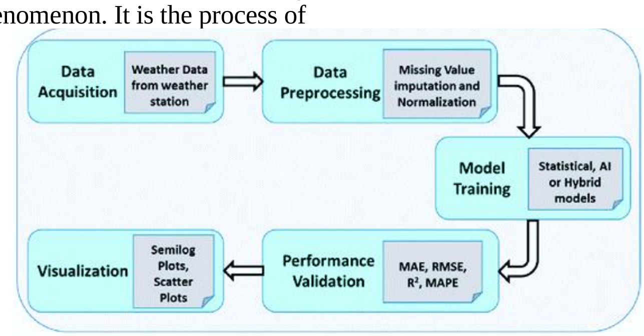

Figure 2. General Framework of Rainfall Prediction

Fig. 2 illustrates the steps involved in rainfall prediction, such as data acquisition, pre-processing, model training, evaluation, and result visualization. Thanks to developments in areas such as cloud computing and the Internet of Things (IoT), meteorological data is now accessible in a variety of forms and in massive quantities. Data pre-processing involves cleaning, integrating, reducing, and transforming the data to improve its quality. This prepares the data for training. Model selection and training are crucial for effective forecasting, followed by evaluation using statistical indicators. The results are then visualized using scatter plots, line plots, and semilog plots to analyze the difference between actual and predicted values.

D. *Agriculture vs. Rainfall Prediction*

The prediction of crop yield and rainfall has become a challenging task for every nation, as it is closely tied to economic growth. Accurate rainfall information is crucial for planning crop planting and estimating crop yield [9]. It also helps in determining the amount of water needed for farming from stored water resources. Agriculture is a key component of the economy, and weather plays a significant role in agricultural production. Previously, farmers relied on their experience to predict rain and manage crops, but now computing technology is essential for efficient estimation of rainfall and crop growth. Weather abnormalities can cause physical damage to crops and soil erosion, making agriculture and rainfall prediction vital for economic development [10].

E. *Traditional Rainfall Prediction*

In the ancient world, observing the weather was a regular part of many people's lives, helping them decide when to go out and what to wear. As early as 650 BC, the Babylonians studied cloud patterns and used astrology to predict the weather. Aristotle referred to these weather patterns as "metrology" or "Metrologica," and Theophrastus compiled a book called "Book of Signs" to showcase weather forecasting techniques. Chinese and Indian astronomers began forecasting weather in 300 BC. Traditional methods of predicting rainfall were based on observations and experiences with animals, plants, insects, meteorological and astronomical indicators, and almanacs [11].

In India, astrology-based studies of clouds, wind examination, and nature observation have been used for over a thousand years to forecast rainfall [12-13]. Ancient texts such as Rig Veda and opening charts contain discussions about rain. Varahamitira (505–587 AD) discussed the science of rain forecasting and assessing it in the unit of adhaka in Brihat Samhita, whereas Chanakya (300 B.C.) outlined rainfall and its measurement. Parashara uses the sun and moon's planetary positions as the basis for her rain predicting method.

Panchangs, public astrological almanacs, were published during the Vedang Jyotish period and were particularly useful to farmers [14]. Panchangs from Varanasi were equivalent to the rainfall recorded by the IMD [15]. Rainfall has been predicted based on the Nakshatras, especially on the ruling planet. For example, Mars represents scanty rainfall, Saturn represents very low rainfall, the Sun represents moderate rainfall, Mercury and Venus represent good rainfall, Jupiter represents very good rainfall, and the Moon represents very heavy rainfall. Rainfall prediction was also based on the observation of wind, air, sky, clouds, plant behavior, and animal behavior [16]. Traditional methods of observing wind and air included features such as the direction of the wind, the direction of smoke from fires, calm conditions, smelling the air, checking humidity, and observing ocean swells. Observing clouds involved analyzing features such as shape [17], position, color, and movement. The observance of the sky included looking for a red sky in the morning, a rainbow in the morning, a ring around the moon at night, and the count of stars at night [18]. Plant behaviors, such as flipped-over leaves, closing pinecones, the smell of flowers before rain, and dry grass in the morning light, were also used as signs of rainfall [19]. In coastal areas, seaweed was used as a natural weather forecaster.

Observing animal behavior was another traditional method, with various behaviors such as cows lying down before rain, sheep huddling before rain or snow, and the behavior of birds, bees, butterflies, snakes, frogs, dragonflies, spiders, wasps, and tortoises all being used as indicators for rainfall [20]. The people of Ladakh rely on astrological concepts from the Tibetan almanac, Lotho, to guide their agricultural activities. The almanac also uses arithmetic principles to predict weather patterns. Angchok and Dubey [21] conducted a study to assess the accuracy of Lotho's predictions for rainfall, and their findings generated interest as the use of astrological concepts from Lotho appeared to closely align with actual weather events. These traditional methods are still used today to predict rainfall, although their accuracy is not always proven. Due to changing climatic conditions, the use of statistical methods-based prediction techniques has been incorporated alongside traditional methodologies.

F. *Statistical Methods-Based Rainfall Prediction*

Statistical modeling involves applying statistical analysis to available data to create a mathematical representation or model of the observed data, providing more accuracy than traditional rainfall methodologies. With an emphasis on rainfall history and monsoon forecast, the IMD was founded in 1875 to study climate-related matters in India.

Early predictions of Indian Summer Monsoon Rainfall (ISMR) were based on factors such as Himalayan snowfall, large-scale pressure patterns like the North Atlantic Oscillation (NAO), North Pacific Oscillation (NPO), and El Nino Southern Oscillation (ENSO), as well as the Darwin Pressure Anomaly (DPA) [22]. Monsoon forecasting mathematics and statistical model development was determined to be computationally intensive and complicated. Numerous factors have been investigated by researchers as potential indications of monsoon rainfall, such as local climates, ENSO signals, cross-equatorial flow, and world weather patterns. There are empirical models that use dynamic methods and time series analysis, such as the General Circulation Model (GCM), although regression models are better for making long-term predictions [23].

Different statistical methods, such as linear prediction models [24], stochastic models [25], and Markov chain models [26], have been proposed for rainfall prediction in various regions. It is well-established that the summer monsoon season is affected by cross-equatorial flow, which is in turn influenced by global circumstances. It is important to discover useful predictors since the efficiency and impacts of these variables can change over time as a result of changes in climatic phenomena including deforestation, pollution, and global warming.

G. *Applications of Artificial Intelligence in Rainfall Prediction*

AI has been widely used in the field of rainfall prediction, utilizing advanced algorithms and data analytics to improve the accuracy and efficiency of forecasting models [27]. Some notable applications include:

- ML models: ML algorithms, such as Decision Trees (DT), Naive Bayes (NB), Random Forests (RFs), Support Vector Machines (SVM), and ensemble methods, have been utilized to analyze historical meteorological data and detect patterns related to rainfall [28]. These models may learn from past data and use the patterns they find to make predictions.
- DL models: Neural networks, especially DL models such as Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), have demonstrated the potential to capture intricate relationships within meteorological datasets. DL can automatically extract pertinent features from data,

making it particularly suitable for tasks such as rainfall prediction [29].

AI techniques play a crucial role in improving rainfall prediction by integrating various data sources such as satellite imagery, weather station data, and atmospheric pressure readings. Early warning systems for severe rainfall, floods, and other weather-related dangers can be developed with this method, which also helps us understand the components that affect rainfall. AI also enhances climate modeling for more accurate long-term forecasts and enables the examination of spatial and temporal patterns in rainfall data [30]. Additionally, AI models can estimate uncertainties in rainfall predictions, providing decision-makers with a nuanced understanding of reliability and confidence levels [31].

In the field of meteorology, accurately predicting rainfall is a significant challenge due to the complex nature of atmospheric phenomena. Precise rainfall forecasts are crucial for sectors such as agriculture, disaster management, and water resource planning. As a result, researchers are increasingly turning to AI methods to analyze meteorological data and uncover patterns. This paper critically examines recent studies that use AI, including ML and DL techniques, to predict rainfall. By exploring the evolving landscape of AI approaches in rainfall prediction, the primary goal is to understand the strengths, limitations, and advancements in these methods. This study not only clarifies the existing situation of the field by examining the publication trajectory, but it also suggests avenues for future research into artificial intelligence-based rainfall prediction.

The following sections are organized as follows: Section II reviews various AI-based rainfall prediction models. Section III concludes the study and suggests potential enhancements for rainfall prediction.

II. SURVEY ON AI-BASED RAINFALL PREDICTION MODELS TYPE STYLE AND FONTS

Rainfall prediction is the subject of this chapter's extensive literature analysis, which delves into the numerous approaches taken by writers. The review encompasses ML and DL techniques employed in the systems developed for this purpose, organized by year of publication.

A. Machine Learning-Based Rainfall Prediction

Heavy rain predictions are made using ML techniques including association, prediction, clustering, regression, classification, and so on. These strategies are useful for figuring out how various parameters relate to one another. This section delves into the latest research on methods that utilize ML to forecast rainfall. In order to predict when rain would fall in the next three to seven days across all seasons, Esteves et al. [32] created a soft computing method that makes use of ANNs. Ten agriculturally important districts in Brazil were selected for their lengthy weather records and absence of reliable climate projections; these regions' time series data formed the basis of the model. As inputs for the ANNs models, it estimated potential evapotranspiration and water balance using 60 years of accumulated precipitation and daily mean air temperature data.

In order to forecast precipitation, Suparta and Samah [33] employed the ANFIS time series approach. As its foundation, the ANFIS model was trained and evaluated with a wide range of input structures and membership functions. The ANFIS time series method was found to be successful for rainfall prediction in an analysis of six years of monthly rainfall data in South Tangerang City, Banten. To forecast yearly precipitation, Diop et al. [34] employed the Multi-Layer Perceptron-Whale Optimization Algorithm (MLP-WOA). The model was created by utilizing three input variables: yearly rainfall at lag 1, 2, and 3, which correspond to Pt-1, Pt-2, and Pt-3, respectively, collected from two synoptic sites in Senegal (Fatick and Goudiry) between 1933 and 2013. Improving the MLP algorithm's accuracy was achieved by utilizing the WOA.

A system for predicting yearly and non-monsoon rainfall was created by Zhang et al. [35] utilizing the Support Vector Regression (SVR) and MLP algorithms. It obtained the relative humidity and total annual rainfall statistics from the Government of Odisha's Department of Forest and Environment from 1991 to 2015. When making predictions about rainfall outside of the monsoon season, factors such average monthly temperature, wind speed, humidity, and cloud cover were taken into account.

In order to improve rainfall prediction, Madhukumar et al. [36] created a hybrid climate learning model that merges climate and DL models. To find the most accurate prediction, they employed a Probabilistic MLP (PMLP) network to compare results from various climate models. The chosen forecast was subsequently sent into an HD-LSTM network, which learns the correlation between the forecast and actual temperature and rainfall data to generate a prediction for the following day.

Researchers Bojang et al. [37] looked at the Deji and Shihmen reservoir basins in Taiwan to see how reliable it was to use Singular Spectrum Analysis (SSA) to preprocess data for monthly rainfall forecasts. In order to improve the accuracy of rainfall predictions, they developed hybrid models (SSA-LSSVR and SSA-RF) by combining SSA with Least-Squares SVR (LS-SVR) and RF. In order to estimate the intensity of rainfall, Liyew and Melese [38] employed ML algorithms to identify pertinent atmospheric variables and utilize them to forecast daily rainfall amounts. Selecting environmental factors to feed into the machine-learning model was done using the Pearson correlation technique.

Anwar et al. [39] used the Extreme Gradient Boosting (XGBoost) method to create a multivariate model for predicting rainfall. The weather station recorded meteorological conditions for seven years, which were used to build the model. Merging Gene Expression Programming (GEP) with Multi-Stage Genetic Programming (MSGP), Danandeh Mehr [40] presented a novel ensemble evolutionary model. Data on precipitation from the Antalya weather station was used to test the model. In order to establish input/output time series for standalone regression models, historical data was gathered and analyzed. Classic Multiple Linear Regression (MLR), MSGP, and GEP were the three models utilized for rainfall forecasting. In the third stage, three ensemble methods called evolutionary ensemble MSGP, linear ensemble model, and arithmetic mean were used to integrate the results from the solo models. A robust hybrid model for precipitation prediction was introduced by Abdul-Kader and Mohamed [41]. For better precision, they mixed MLP with Particle Swarm Optimization (PSO). They trained MLP using PSO instead of gradient descent backpropagation. A machine-learning fusion approach was created by Rahman et al. [42] to create a smart city rainfall prediction system that works in real-time. They made use of support vector machines, K-nearest neighbors, DT, and NB. They combined the prediction accuracies of the various algorithms using a fuzzy logic strategy to increase accuracy. Prior to categorization, the system utilized pre-processing methods like cleaning and normalization on twelve years of Lahore historical meteorological data (2005–2017).

One study that used the ANFIS to forecast monthly rainfall averages was that of Rao et al. [43]. Several surface meteorological indicators were taken into account as potential predictors within the 17,504 km2 Upper Brahmani Basin. In order to create an ANFIS model for rainfall forecasting, the research used 37 years of climatic data, spanning 1983–2020. The study area's best accurate forecasts were produced by the hybrid model, which included six membership functions. The goal of the hybrid model created by Jayasree et al. [44] was to improve the accuracy of yearly rainfall predictions by combining RF with Empirical Mode Decomposition (EMD). The rainfall signal was broken down into six Intrinsic Mode Functions (IMFs) using the EMD approach in order to reveal hidden patterns. Afterwards, predictions were generated using the IMFs by means of the RF algorithm. Yearly rainfall data from 1871 to 2020 for Kerala was used to train and evaluate the hybrid RF-IMF model.

In order to forecast the status of the following day's rainfall using meteorological data gathered in Australia from 2007 to 2017, Tuysuzoglu et al. [45] implemented an EK-stars method. Sunshine, humidity, pressure, and temperature were all included of the data set. For the purpose of constructing and integrating several classifiers for the purpose of rainfall prediction, the study also presented the probability-based aggregating (pagging) method. Changing input settings, utilizing alternative approaches in the pagging step, and performing feature selection were all part of the experimental setups that were used to execute the EK-stars.

Allawi et al. [46] developed a strong method for detecting nonlinearity in rainfall patterns by integrating various optimization algorithms with ANN. A real-world case study was conducted in Malaysia, using 54 years (1967–2020) of local monthly data to create an ANN model for real-time rainfall forecasting. Different network types and input information were evaluated to produce accurate forecasts, and statistical analysis was used to assess the model's accuracy in predicting rainfall.

Hassan et al. [47] conducted a study aimed at developing a highly accurate rainfall prediction model using ML and feature selection algorithms. In order to evaluate the prediction models, they combed through data collected from weather stations all around Australia and extracted the most important meteorological characteristics to use as input variables. Prior to data analysis, the researchers used Principal Component Analysis (PCA) to pre-process the dataset and identify the most important aspects. They then used SN, DT, SVM, RF, logistic regression, and other ML algorithms to forecast the future.

Table I compares the ML algorithms used in the above-discussed studies for rainfall prediction. Different evaluation metrics are considered to assess the model prediction performance, as defined below.

- Mean Square Error (MSE): It is computed by

$$MSE = \frac{1}{n}\sum_{k=1}^{n}\left(y_{pred} - y_{obs}\right)^2 \quad (1)$$

In Equation (1), y_{pred} and y_{obs} denote the values of predicted outcomes and observations, respectively, and n refers to the total amount of data.

- Root Mean Square Error (RMSE): It is calculated as follows:

$$RMSE = \sqrt{\frac{1}{n}\sum_{k=1}^{n}\left(y_{pred} - y_{obs}\right)^2} \quad (2)$$

- Correlation coefficient (R): It is computed as:

$$R = \sqrt{1 - \frac{\sum_{k=1}^{n}\left(y_{obs} - y_{pred}\right)^2}{\sum_{k=1}^{n}\left(y_{pred}\right)^2}} \quad (3)$$

$$R^2 = 1 - \frac{\sum_{k=1}^{n}\left(y_{obs} - y_{pred}\right)^2}{\sum_{k=1}^{n}\left(y_{pred}\right)^2} \quad (4)$$

- Mean Absolute Percentage Error (MAPE): It is determined as follows:

$$MAPE = \frac{1}{n}\sum_{k=1}^{n}\left(\frac{y_{pred}(k) - y_{obs}(k)}{y_{pred}(k)} \times 100\%\right) \quad (5)$$

- Mean Absolute Error (MAE): It is computed by

$$MAE = \frac{1}{n}\sum_{k=1}^{n}\left|y_{pred} - y_{obs}\right| \quad (6)$$

- Nash-Sutcliffe model Efficiency (NSE): It is calculated as follows:

$$NSE = 1 - \frac{\sum_{k=1}^{n}\left(y_{obs} - y_{pred}\right)^2}{\sum_{k=1}^{n}\left(y_{obs} - \overline{y_{pred}}\right)^2} \quad (7)$$

In Equation (7), $\overline{y_{pred}}$ is the mean value of predicted outcomes.

- Accuracy: It measures the number of exactly predicted instances to the total instances.

$$Accuracy = \frac{True\ Positive\ (TP) + True\ Negative\ (TN)}{TP + TN + False\ Positive\ (FP) + False\ Negative\ (FN)} \quad (8)$$

- Precision: It is computed by

$$Precision = \frac{TP}{TP + FP} \quad (9)$$

- Recall: It is calculated as follows:

$$Recall = \frac{TP}{TP + FN} \quad (10)$$

- F1 score: It is determined as:

$$F1 = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (11)$$

Table I. Comparison of Machine Learning-Based Rainfall Prediction Models

Ref. No.	Algorithms	Benefits	Limitations	Data Source/Study Area	Evaluation Metrics
[32]	ANN	Its peak performance occurred over clearly defined seasons.	During times of seasonal change and in locations affected by macro- and mesoclimatic factors, its accuracy was diminished.	Sites of conventional weather stations located on the ground in Brazil	Mean accuracy: Summer = 78%; Winter = 71%; Spring = 62%; Autumn = 56%
[33]	ANFIS	The results were promising, with 80% of the data testing being accurately predicted.	It was limited by the presence of NaN (Not a Number) or blank data in time series, as well as by highly volatile or extreme data	Data acquired from MCGA (Meteorology, Climatology, and Geophysics Agency) or	RMSE = 9.893; MSE = 0.125; MAPE = 1.094;

			characteristics, which can result in low predictive accuracy.	BMKG (Badan Meteorologi, Klimatologi dan Geofisika in South Tangerang City located in Pondok Betung	
[34]	MLP-WOA	The accuracy was slightly improved.	In contrast to the training phase, the testing phase does not have access to some crucial time series data.	Annual rainfall data of Fatick and Goudiry Station in Senegal	Fatick station: RMSE = 130; R = 0.69; Goudiry station: RMSE = 105.9; R = 0.65;
[35]	SVR and MLP	High accuracy and better generalizability.	It was not suitable for multiple or multivariate time-series prediction.	Data obtained from 1991 to 2005 in Odisha, India	SVM: R = 0.9989 RMSE = 0.1024; MAE = 0.085; MLP: R = 0.9913 RMSE = 0.1874; MAE = 0.169;
[36]	PMLP and HD-LSTM	Low RMSE and high correlation.	It lacks more important weather parameters.	Dataset from the Australian Bureau of Meteorology (BOM) for the Burdekin area in Queensland	RMSE = 3.51
[37]	SSA-LSSVR and SSA-RF	It can efficiently predict monthly rainfalls.	The utilization of monthly rainfall data from only two reservoir watersheds severely restricted the generalizability.	Taiwanese reservoir watersheds Deji and Shihmen: monthly rainfall forecasting.	SSA-LSSVR (for Deji watershed): RMSE = 75.29; NSE = 0.86 SSA-LSSVR (for Shihmen watershed): RMSE = 132.81; NSE = 0.67 SSA-RF (for Deji watershed): RMSE = 121.76; NSE = 0.63 SSA-RF (for Shihmen watershed): RMSE = 98.75; NSE = 0.82
[38]	Pearson correlation, MLR, RF, and XGBoost	It was better suited to predict daily rainfall using specific environmental features.	Accuracy can only be enhanced using sensor and meteorological datasets that include supplementary environmental information.	Dataset obtained from the local meteorological office at Bahir Dar City, Ethiopia	RF: MAE = 4.49; RMSE = 8.82 MLR: MAE =4.97; RMSE = 8.61 XGBoost: MAE = 3.58; RMSE = 7.85
[39]	XGBoost	Low RMSE and MAE.	Overfitting problem has affected the accuracy.	Daily weather data collected from the Indonesian Meteorology, Climatology, and Geophysics Agency (BMKG) for Tanjung Mas, Semarang City	Training RMSE = 2.75; Testing MAE = 8.8
[40]	Ensemble MSGP (EMSGP)	Better accuracy.	The analysis was limited to using historical seasonal rainfall as predictors, and the nonstationary feature of the seasonal rainfall series was not taken into consideration.	Rainfall data obtained from Muratpasa meteorology Station in Antalya downtown	EMSGP: RMSE = 0.086; NSE = 0.674; MAPE = 0.264
[41]	PSO-MLP	Low RMSE values.	It needs more weather parameters to enhance prediction performance.	Weather data of 2009 for New Capital Management through the Automatic Weather Station (AWS)	RMSE = 0.14
[42]	Fused ML	Better prediction performance.	No one can have faith in the outcome of a prediction if the data used to make it is in any way corrupted.	Lahore, Pakistan, weather records over 12 years (2005–2017)	Accuracy = 0.94; Recall = 0.34
[43]	ANFIS	It has a respectable track record of accurately predicting monthly average rainfalls.	A major issue is the absence of information regarding future rainfalls.	37 years of weather data (1983-2020) for the Upper Brahmani Basin in India	MSE = 0.003; MAPE = 5.09
[44]	EMD-RF	It can be utilized to effectively forecast the annual rainfall.	It needs to integrate more weather parameters to enhance the prediction performance.	Kerala yearly rainfall dataset for the years 1871–2020	MAE = 19.7; MSE = 24.6; RMSE = 4.9;

					MAPE = 7%; R^2 = 0.76
[45]	EK-stars	Better accuracy.	The study failed to pay attention to how rainfall varies among locations throughout the year.	Meteorological data obtained from 2007 to 2017 in Australia	Mean accuracy = 81.86%
[46]	ANN	It can predict monthly rainfall with satisfactory accuracy.	It did not obtain the global optima. Also, it was not suitable for time-series data.	Local monthly weather data between 1967 and 2020 in Malaysia	RMSE = 10.42; MAE = 10.78; NSE = 0.91
[47]	PCA and ANN	Better accuracy.	One drawback was using past weather records, which might not fully capture the intricacy of modern weather systems.	Consistent meteorological data gathered from 49 weather stations in Australia from 2008 to 2017.	Accuracy = 91%; Precision = 88%; Recall = 89%; F1-score = 89%.

B. *Deep Learning-Based Rainfall Prediction*

Rainfall forecasts using DL have recently attracted a lot of attention from researchers because, when compared to more conventional ML methods, DL significantly improves prediction accuracy and reliability. DL outperformed other methods in rainfall prediction due to its capacity to learn intricate patterns from massive datasets. Here we will take a look at some recent research on methods that use DL to forecast when it will rain.

An improved method for predicting rainfall was proposed by Poornima and Pushpalatha [48] using weighted linear units in an Intensified LSTM-based RNN. This model utilizes the LSTM network, multiplies the input sequence to the layers of LSTM, and employs the Adam Optimizer to solve capacity insufficiency, vanishing gradient, and prediction inaccuracy. In order to anticipate the daily rainfall in multiple steps ahead of time, Khan and Maity [49] combined MLP with one-dimensional CNN (Conv1D). Inputs to the model came from a GCM simulation and included nine meteorological variables linked to daily rainfall variance.

An LSTM-based correction model for rainfall prediction utilizing several meteorological parameters was created by Zhang et al. [50]. Daily weather predictions were the target of the study's efforts to increase forecast accuracy. To ensure the accuracy of the method, it was tested using historical data from control forecasts produced by the European Centre for Medium-Range Weather Forecasting (ECMWF). A correlation analysis with real-time rainfall led to the selection of eight important meteorological parameters. In order to improve weather predictions for eastern China, the samples were first clustered using K-means and then modeled using LSTM. The model was fed the eight main meteorological variables, and the output was the discrepancy between the actual rainfall and the rainfall predicted by the model.

In order to forecast Thailand's precipitation, Manokij et al. [51] built a deep-learning system that integrates Convolutional Neural Network (CNN) and Gated Recurrent Unit (GRU) models. The framework takes regional rainfall trends into account while building a model for each area. Using CNN and focus loss, we were able to resolve data imbalances and categorize rain and non-rain occurrences. In order to adapt GRU's anticipated range for rainfall, autoencoder loss was employed. Making use of El-Nino and Indian Ocean Dipole (IOD) data, Haq et al. [52] employed LSTM to forecast rainfall in Sidoarjo, East Java. In order to forecast the rainfall data for the sixth week, they utilized factors from the previous five weeks. The use of LSTM as a generator and CNN as a discriminator to forecast rainfall data was demonstrated by Venkatesh et al. [53] in their presentation of rainfall prediction in the India region using Generative Adversarial Network (GAN).

A chaotic rainfall prediction system was created by Billah et al. [54] using an LSTM model driven by historical datasets. In order to predict when it might rain, the researchers first used a two-layer LSTM model after selecting the most important features. Using deep reinforcement learning, Nithyashri et al. [55] created a model to predict coastal areas' rainfall based on the Internet of Things. Data on rainfall in coastal areas of India was analyzed using LSTM networks to identify temporal connections. In four sub-catchments of Samar, Philippines, Necesito et al. [56] investigated time series modeling. In order to create a hybrid signal that combines a "smoothened" or "denoised" signal with a "detailed" or "noise" signal, they used the Discrete Wavelet Transform (DWT) technique on the rainfall time series. For the purpose of predicting precipitation, they also employed the univariate LSTM network model.

A GRU-based encoder, attention strategy, GRU-based decoder, and anticipated gradient-based explanation modules were introduced by He et al. [57] to create an explainable DL model for monthly rainfall prediction. The first three modules build an attention-based encoder-decoder to forecast monthly rainfall for a number of consecutive months in the future, while the last module assigns attribution values to the input climate and weather variables to measure their importance. Table II presents a comparison of the research that have been mentioned above that have used DL models to forecast rainfall.

In summary, Table I and Table II provide a comprehensive review of various ML and DL algorithms used for predicting rainfall. Each algorithm has its strengths and weaknesses, highlighting the complexity of rainfall prediction. The evaluation of these algorithms in previous studies has focused on metrics such as RMSE, MAE, R, and accuracy. Fig. 3(a) – 3(d) has been plotted to illustrate the significance of selecting the most suitable algorithm based on specific context and data characteristics. It indicates that DL algorithms achieved a higher performance compared to the ML methods, for e.g., [53] achieves the maximum accuracy, [57] attains better R value, [40] reaches a minimum RMSE, and [35] attains a minimum MAE. On the other hand, as the field advances, it is important to develop ensemble models like DL with attention strategies and optimization schemes to improve predictive models by including more weather parameters. This will lead to better accuracy in rainfall forecasts.

Table II. Comparison of Deep Learning-Based Rainfall Prediction Models

Ref. No.	Models	Benefits	Limitations	Data Source/Study Area	Evaluation Metrics
[48]	Intensified LSTM	Minimum RMSE, training time and loss.	It needs more weather parameters to improve the accuracy.	Rainfall data obtained from 1980 to 2014 in Hyderabad	Accuracy = 88%; RMSE = 0.33

[49]	Conv1D and MLP	Better prediction performance.	It needs hybrid models to simulate rainfall field prediction instead of point rainfall.	Weather data collected for 12 cities in Maharashtra, India from 1941 to 2005	RMSE = 24.19; NSE = 0.11; R = 0.55
[50]	LSTM	It can achieve effective correction of model-forecast rainfall.	It did not analyze the relationship between site-specific rainfall and forecasted rainfall in the surrounding area, leading to low TS for moderate and heavy rain.	The Central Meteorological Observatory of Shanghai provided rainfall data obtained from automated stations in China.	RMSE = 7.45
[51]	CNN and GRU	During mild to moderate rain periods, it might decrease error values for rainfall prediction.	Due to the small size of the data points, it is unable to detect rainfall during intense rain periods.	Hourly rainfall data collected from the Hydro-Informatics Institute, Thailand from 2012 to 2018	Mean RMSE = 1.2323; Mean F1-score = 47.18%
[52]	LSTM	It achieved the lowest MAAPE.	It needs additional climate factors to improve the model generalizability.	El-Nino Index 3.4 and IOD weekly data collected from the BOM between December 2014 and August 2019	Mean Arctangent Absolute Percentage Error (MAAPE) = 0.581
[53]	GAN	The maximum prediction accuracy was achieved.	The training stage requires more time and computing resources.	Rainfall data obtained from the official website of the Indian government.	Accuracy = 99%
[54]	2-layer LSTM	High accuracy.	Limited dataset and it needs to implement Bidirectional LSTM (Bi-LSTM) to achieve the maximum performance.	Rainfall data collected from the Bangladesh Meteorological Department (BMD)	Accuracy = 97.14%
[55]	LSTM	Low RMSE, MAE and loss.	A few different parameters were needed to incorporate as contributions for rainfall forecasts.	Rainfall data obtained from the coastal areas of India	Mean accuracy = 89%; RMSE = 0.75; MAE = 0.13;
[56]	DWT and univariate LSTM	It provide efficient and time-bound results for flood-prone countries, where there is a lack of hydrological data.	Advanced deep-learning models are required to learn spatiotemporal correlations among various weather factors across different time scales.	Rainfall data collected from the Advanced Science and Technology Institute (ASTI) in Philippines	RMSE = 0.2; NSE = 0.93; R = 0.96
[57]	Attention-strategies and explainable modules for a GRU-based encoder-decoder	It has the potential to enhance the precision of multi-stage rainfall forecasting.	Due to the weather stations' restricted availability of meteorological parameters, the generalizability was low.	Average rainfall in Australia from 1981 to 2010	Darwin city: $R^2 = 0.835$; MAE = 39.903 Perth city: $R^2 = 0.796$; MAE = 20.884

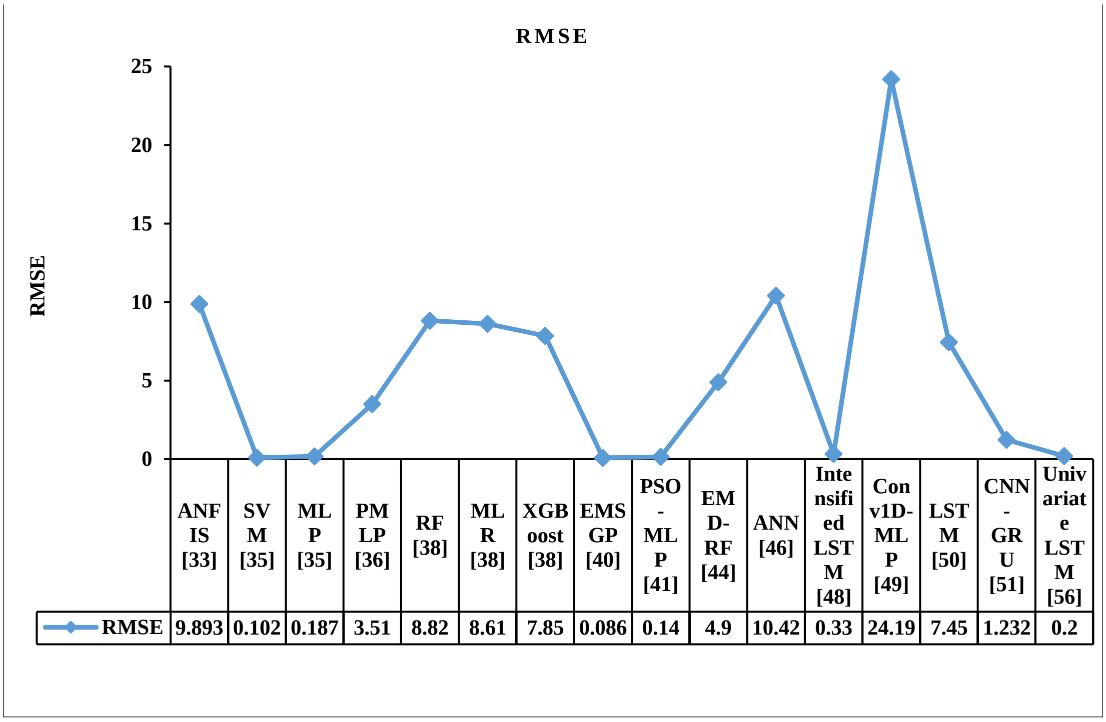

Figure 3(a). Comparison of RMSE for Different Prediction Models

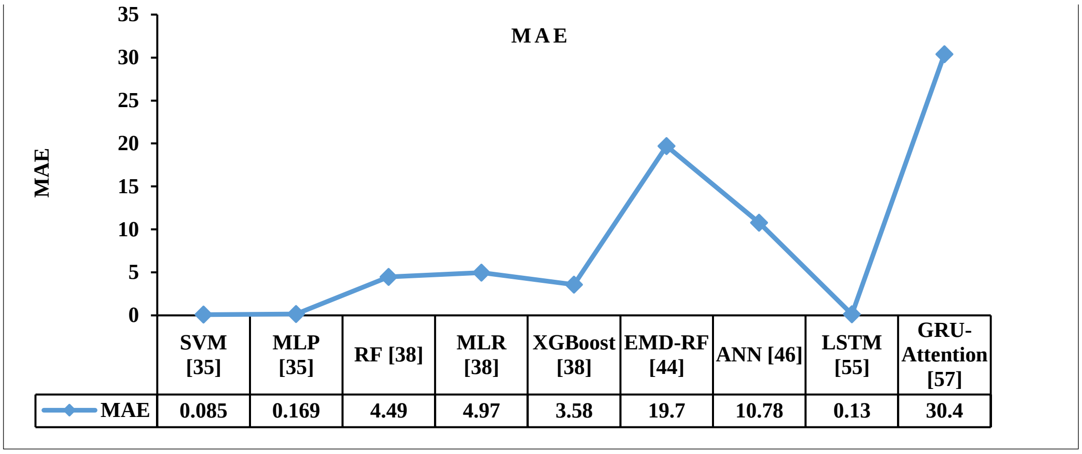

Figure 3(b). Comparison of MAE for Different Prediction Models

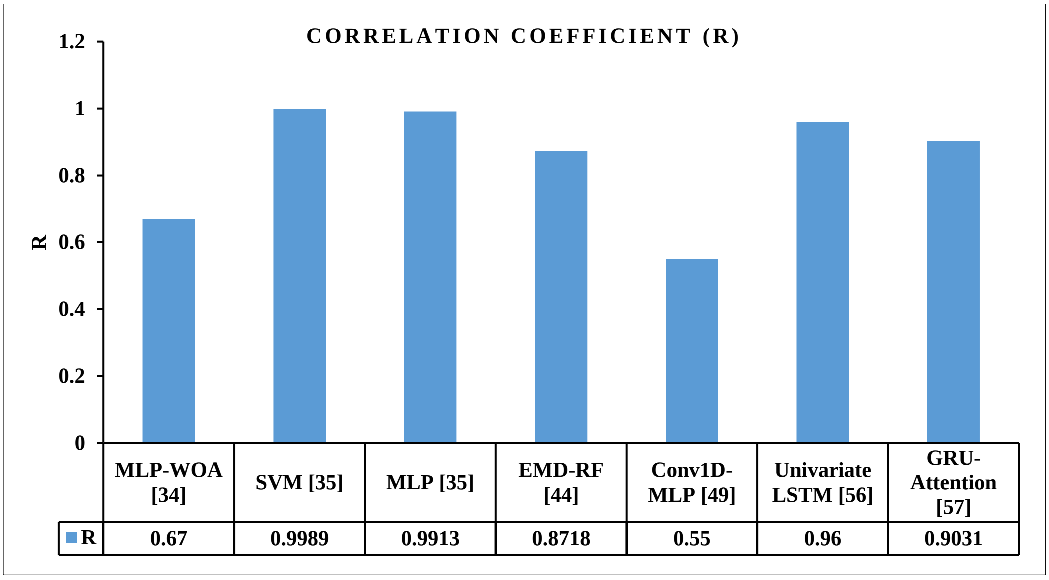

Figure 3(c). Comparison of R for Different Prediction Models

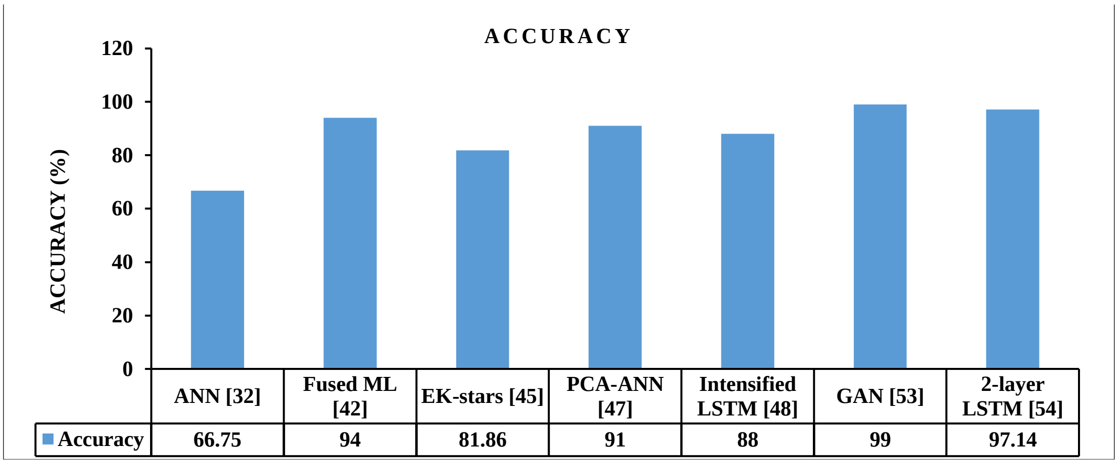

Figure 3(d). Comparison of Accuracy for Different Prediction Models

III. CONCLUSION

A survey of current research on artificial intelligence (AI) for weather prediction is presented in this article. The study aims to improve the accuracy of rainfall predictions compared to current models by analyzing data. The study found that DL is more effective than ML for predicting rainfall, highlighting the importance of using advanced AI techniques to improve prediction accuracy, particularly for agriculture. Future works could involve incorporating almanac or Panchang data alongside traditional weather factors to improve prediction accuracy, providing a more holistic understanding of the complex dynamics influencing rainfall. Many industries rely on reliable weather predictions, and this new method could help shed light on precipitation patterns more thoroughly.

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