Comparative Analysis of Different Weather Prediction Models

Piyush Raj[a], Aditya Mishra [a]

[a] *Department of Information Technology, Indian Institute of Information Technology, Sonepat, India*

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ABSTRACT

In modern times, accurate weather prediction plays very important role in many sectors such as agriculture, transportation, aviation, and disaster management. Traditional methods of weather prediction, including Numerical Weather Prediction (NWP) models, always struggle to handle the complex, nonlinear, and high-dimensional nature of weather dataset. These challenges of the weather data reduces their effectiveness, especially in short-term forecasting. With the exponential growth availability in the weather data, the Artificial Intelligence (AI), especially Machine Learning (ML) models seem so promising for weather prediction systems. This research is oriented toward evaluating and comparing the performance of four supervised machine learning models--Logistic Regression, Support Vector Machine (SVM), K-Nearest Neighbors (KNN), and Random Forest, in predicting the possibility of precipitation based on the real-world meteorological data. The dataset used in this study contains of key atmospheric parameters such as temperature, humidity, precipitation, wind speed, and wing direction. Before training the models on the dataset, dataset preprocess using steps such as handling missing values, feature engineering, and standardization to ensure consistency and improve model performance. Each model's performance and effectiveness was evaluated using various evaluation matrices such as Accuracy, F1-score, Precision, Recall, and Root Mean Square Error (RMSE). Among these models, the Random Forest classifier shows the best overall performance, achieving an **accuracy of 98%, F1-score of 0.89**, and **precision of 0.93**. This shows **10-18%** improvement in accuracy and classification balance compared to the baseline models. The Support Vector Machine (SVM) shows the highest precision but it is only effective in identifying majority classes, struggles with minority classes. K- Nearest Neighbor (KNN) performs moderately well in identifying local data trends but suffers from scalability issues. Logistic Regression is interpretable in nature but it suffers in handling non-linear patterns common in weather data. The results highlight the capability of ensemble learning methods like Random Forest in modeling complex weather systems and producing dependable forecasting systems. The study also aims to provide a foundation for future work in intelligent weather prediction such as integration with deep learning models and real-time adaptive systems for better response to dynamic climate conditions.

1. Introduction

Weather forecasting has been very interesting and research subject from the starting due to its critical role in day-to-day life and its crucial effect on several socio-economic activities. The accuracy of weather prediction system directly effects sectors such as agriculture, transportation, disaster management, construction, energy, sports, and tourism. As the climate patterns are shifting continuously due to climate change, the reliable weather forecasting systems have become very important. Rainfall prediction is very important for the agricultural planning, flood prevention, water resource management, and avoiding of hazard caused by climate. Even there is advancement in the observational tools and numerical simulations, weather forecasting is still a field of challenge due to chaotic and nonlinear behaviour of atmosphere.

Traditionally used Numerical Weather Prediction (NWP) models for the weather prediction use physical and mathematical formulations to simulate atmospheric processes. These models takes data from various sources such as satellite, ground stations, and radar systems, to produce forecasting systems. Although Numerical Weather Prediction (NWP) models provide a physically close approach and can provide reliable large-scale predictions, they have several limitations. First, they depend on initial conditions and complex boundary equations makes them error prone to very small measurement errors. Second, they require very high computational resources and in most of times not suited for real-time or short-term forecasting. Finally, their performance decline when they are used to highly localized predictions or when nonlinear dependencies are present in atmospheric variables. These challenges highlight the requirements of alternative approaches, which can increase the accuracy and responsiveness of forecasting systems.

In recent years, the Artificial Intelligence (AI) has been applied to various fields, and weather prediction is one them. Within AI, Machine Learning (ML) techniques rise as very important tools for detecting the patterns and making predictions on the basis of historical data. Unlike several NWP models, ML algorithms first detect the hidden patterns and trends that may be difficult to represent through explicit equations. ML models are most suitable for high-dimensional and non-linear datasets, which are common in real-world. ML models can also be updated with new data, making them most suitable for evolving weather conditions and data collection techniques.

Among the various ML Approaches, supervised learning techniques have become very popular in prediction tasks. These methods first train a model using labelled data to make predictions about future or rest of the data instances. For weather prediction task, this generally predicts a target variable--such as rainfall occurrence, temperature, humidity, or wind speed--based on various atmospheric input features. The most usefulness of supervised learning lies in its ability to give both classification (e.g., rain vs. no rain) and regression outputs (e.g., expected rain amount), on the basis of nature of task.

This research particularly focuses on the task of binary rainfall prediction--predicting whether or not there is rainfall on a given day--using four famous supervised learning algorithms: Logistic Regression, Support Vector Machine (SVM), K-Nearest Neighbor (KNN), and Random Forest Classifier. These models have been widely used in machine learning for classification problems and have different strengths and weaknesses.

Logistic Regression is most simple and interpretable model used for binary classification. It is used to define the probability of a binary outcome using a logistic function applied to a linear combination of input classes. As Logistic Regression is computationally very efficient and easy to implement, it only wants to be applied on linear relationship between input variables, which may not always be correct in complex real-world scenarios. As a result, Logistic Regression's ability to deal with nonlinear data is limited.

Support Vector Machine (SVM) is a more advanced model that targets to find an optimal hyperplane that divides different classes in the feature space. SVMs are specially useful in high-dimensional spaces and can be used to nonlinear classification tasks using various kernel functions such as radial basis function (RBF) kernel. However, they need careful parameter tuning and are computationally very expensive for large datasets. Despite this, their robustness and precision make them useful for structured classification tasks, including rainfall prediction task.

K-Nearest Neighbor (KNN) is an instance-based machine learning algorithm that classifies new instances based on the majority class of the 'k' nearest neighbors in the training dataset. It is easy to understand and also perform well when data is well distributed. However, its performance is highly depends on the choice of 'k', distance metric, and feature scaling. Moreover, SVM has high computation cost during prediction time, particularly for large dataset, as it keeps all training instances in memory.

Random Forest is an ensemble learning technique that constructs a structure formed by combination of decision trees during training and collects their predictions to classify new instances. This method is known for its fault tolerant nature, ability to reduce risk of overfitting, and excellent performance on both linear and nonlinear data. Random forest has less effect of outliers and feature scaling, and they shows the importance of feature, which is very helpful in their interpretability. However, this model can become complex and occupy high memory, especially with large ensemble.

This study aims to systematically compare the predictive performance of these four models on a real-world meteorological dataset. The dataset used in this study includes feature such as minimum and maximum temperature, humidity, wind speed, wind direction, atmospheric pressure, and rainfall, along with a binary target variable showing whether it rained on a particular day. Prior to modeling, the dataset was preprocessed using standard techniques, including missing value imputation, feature scaling, and transformation of categorical variables. The models were then trained on 80% of the data and evaluated on the remaining 20% using common performance metrics: Accuracy, F1-Score, Precision, Recall, R^2 Score, and Root Mean Squared Error (RMSE). Additionally, confusion matrices were used to visualize the classification performance of each model.

Initial results revealed that the Random Forest model outperformed the other three in terms of accuracy, robustness, and generalization ability, achieving an accuracy of 98%, an F1-score of 0.89, and a precision of 0.93. SVM followed closely in terms of precision but lagged in recall, indicating it was more conservative in predicting the minority class (rain). KNN provided reasonable accuracy but exhibited sensitivity to hyperparameters and data distribution. Logistic Regression, although interpretable and fast, failed to capture nonlinear interactions, leading to relatively lower performance.

These findings hold significant implications for the development of more reliable weather forecasting tools. By identifying the most suitable machine learning model for rainfall prediction, this research can assist policymakers, researchers, and system developers in building predictive systems that are both accurate and computationally feasible. Furthermore, the comparative nature of this study provides a foundation for hybrid or ensemble models that combine the strengths of individual algorithms. For example, integrating Random Forests with temporal deep learning models like Long Short-Term Memory (LSTM) networks may enhance both spatial and temporal forecasting capabilities.

The remainder of the paper is organized as follows. Section 1 presents a detailed review of recent studies and related work, emphasizing the strengths, limitations, and gaps in existing research. Section 2 describes the methodology, including data preprocessing steps, model configurations, and evaluation metrics. Section 3 provides an in-depth analysis of experimental results and visualizations such as confusion matrices, scatter plots, and performance graphs. Section 4 summarizes the study's conclusions and suggests directions for future research.

1.1. Motivation

Weather forecasting plays a critical role in supporting decisions across multiple sectors, particularly in agriculture, aviation, water management, transportation, energy production, and disaster preparedness. Among the various meteorological events, rainfall prediction holds substantial significance due to its impact on crop yields, water supply, and flood control. Accurate rainfall forecasts can help minimize economic losses, improve infrastructure planning, and save lives during extreme events. However, achieving high accuracy in short-term rainfall prediction is highly challenging.

Traditional weather prediction system depends heavily on Numerical Weather Prediction (NWP) models, which simulate various atmospheric parameters using complex different equations derived from physics. These NWP models are effective for medium- and long- term forecasting, these models have high computation cost and generally fail to provide precise short-term and localized predictions. Moreover, the performance of NWP models decline with the rapid change in the environmental conditions or in the presence of noisy or incomplete data. As global climate patterns become very unpredictable due to this there is an urgent requirement to increase prediction techniques.

Over the past decade, the application of Artificial Intelligence (AI), especially Machine Learning (ML) has increased rapidly and it rises as a powerful tool for modeling complex systems and identifying patterns from large datasets. Machine Learning models can learn from historical real-world data without any significant assumptions about atmospheric pattern, making them most suitable for forecasting problems having high variation and nonlinearity. A large number of studies shows the potential of Machine Learning algorithms in weather related tasks, ranging from temperature prediction to cyclone path prediction. However, there is no record that demonstrate which machine learning technique performs best under which specific climatic conditions or for which particular prediction tasks, when considering interpretability, computational efficiency, and accuracy as crucial factors.

This deficiency of standardization brings a gap in the research and derives a thorough, comparative analysis of most generally used Machine Learning models for rainfall prediction. Each models have their different mathematical foundations, assumptions, and operating characteristics. For instance, Logistic Regression is interpretable and computationally simple but struggles with nonlinear data. SVM offers robustness and precision but requires careful kernel selection and tuning. KNN can detect local patterns effectively but scales poorly with large datasets. Random Forest excels in handling noise and variable importance but may become less interpretable in larger ensembles. Given these differences, there is a pressing need to evaluate these models under a common framework using real-world data and standardized performance metrics.

This study is motivated by the goal of identifying the most suitable ML model for short-term rainfall forecasting through a structured comparison of these four algorithms. By doing so, the research aims to provide practical guidance for researchers, data scientists, and policymakers in building more accurate, efficient, and scalable weather prediction systems. In addition, understanding the strengths and weaknesses of each model will provide a path for developing hybrid or ensemble systems that combine the advantages of multiple algorithms, finally increasing the precision and dependability of AI-based real-world forecasting.

1.2. Related work

Recent advances in machine learning (ML) have provided powerful tools for improving weather prediction accuracy, particularly in rainfall forecasting. Traditional NWP models fail to model the nonlinear and chaotic behaviour of atmospheric data. As a result, research took a turn toward the supervised Machine Learning algorithms to increase the forecasting precision and accuracy.

Jain et al. [1] used the SVM to predict rainfall patterns using labeled real-world weather datasets. Their research shows that SVM could perform better than traditional statical models, particularly in identifying nonlinear patterns. However, model perform very bad with imbalanced data, leading to decreased sensitivity in minority class identification. This study highlights the requirement for balancing strategies and kernel optimization in future work.

Sharma and Gupta [2] applied Random Forest for temperature and humidity prediction, finding its potential in handling noise and multicollinearity. Their study shows that ensemble learning is able to maintain stability across variable conditions. Still, this study is not applied in real life, and the feature engineering process was done manually. If we would able to automate the preprocessing then model's robustness can be enhance.

Zhang et al. [3] used K-Nearest Neighbors (KNN) algorithm for rainfall prediction. Their study uses the local data distribution to predict regional occurrence of rainfall with moderate accuracy. however, KNN's dependency on the distance metrics makes its computation cost high for large scale datasets. KNN also require very high feature scaling for maintain scalability.

Das et al. [4] gave a hybrid ensemble regression framework for weather parameter prediction. The framework integrate multiple Machine Learning algorithms for better generalization and prediction accuracy. While it got good output in non-changing datasets, the model does not have adaptability in real-time environments. Future work on this model could be exploring retraining capabilities on dynamic data.

Taobei Li [5] conducted a comparative analysis involving Linear Regression, Random Forest Regression, SVR, and KNN for temperature prediction. Their study found Random Forest to be the most accurate, but also noted its high training cost. The data used was geographically constrained to England, reducing the model's global applicability.

Hussain et al. [6] developed an ensemble model combining Logistic Regression, Random Forest, and SVM for rainfall classification. Their hybrid method improved prediction accuracy significantly. However, the model became computationally expensive and required substantial parameter tuning. The study revealed a trade-off between accuracy and efficiency.

Sutanto et al. [7] compared Logistic Regression, SVM, Random Forest, and KNN for environmental classification tasks. Although the domain was water quality, the findings are relevant to weather classification due to similar feature structures. Random Forest delivered the best balance between precision and recall. However, model interpretability remained a concern.

Biswas et al. [8] provided a detailed survey of ML-based weather prediction, categorizing models by their mathematical foundation and forecasting capability. Though the paper offered comprehensive theoretical insight, it lacked experimental validation. This limits the ability to assess real-world feasibility. Practical benchmarking remains a gap in such literature.

Ireland et al. [9] used supervised learning methods to detect flooded regions from satellite imagery. While not directly predicting rainfall, their techniques—especially Random Forest—are transferable to meteorological applications. The study suffered from low-resolution satellite data, impacting model precision. Integration with ground data could enhance prediction fidelity.

Wu and Chau [10] introduced modular soft computing methods for rainfall time series prediction. Their system demonstrated improved scalability and interpretability compared to monolithic models. However, it required careful architecture design and extensive training. Its performance in extreme weather events was not fully evaluated.

Pham et al. [11] combined Random Forest and Least Squares SVM to improve extreme rainfall prediction in downscaling tasks. Their hybrid approach was particularly effective in capturing high-intensity rainfalls. Nonetheless, it was validated only in specific regions, raising questions about its generalizability. Incorporating more diverse climate zones is essential.

Ghosh et al. [12] used an ensemble learning strategy combining multiple classifiers to predict rainfall during monsoon seasons. Their method yielded better performance than individual models. The downside was the increased model complexity and difficulty in interpretation. Simplified ensembles could offer a middle ground.

Liyew and Melese [13] evaluated daily rainfall forecasting using ML models such as Decision Trees and Random Forest. Their research confirmed Random Forest's superiority, especially on balanced datasets. However, the models were not tested under seasonally variant data. Seasonal tuning could further enhance model adaptability.

Yen et al. [14] applied deep learning techniques like LSTM to predict rainfall in southern Taiwan. These models performed well on sequential data but required substantial computational resources. The training time was notably longer compared to traditional models. Deployment in low-resource settings remains challenging.

Dotse et al. [15] reviewed hybrid ML models for improving rainfall prediction. They emphasized the importance of combining statistical and data-driven methods. Though conceptually sound, the paper lacked prototype implementation. Bridging this theory-practice gap is necessary for real-world impact.

Latif et al. [16] evaluated ML and remote sensing integration for rainfall estimation. Their results showed that satellite-enhanced data improved model precision. However, spatial resolution limitations reduced accuracy in localized forecasting. Further improvements in data granularity are needed.

Kumar et al. [17] benchmarked various ML models for rainfall prediction across Indian cities. SVM and Random Forest emerged as top performers. The study lacked a comprehensive hyperparameter tuning process. This left room for further optimization in model performance.

Markuna et al. [18] explored the use of ML for long-term rainfall forecasting. Their study showed that ensemble methods outperformed individual classifiers. However, the models were not interpretable, which is a concern for policy applications. Emphasis on explainable AI is needed.

Sarasa-Cabezuelo [19] applied Random Forest to Australian rainfall datasets and demonstrated consistent accuracy. The study faced challenges with seasonal imbalance in the data. Techniques like SMOTE could be used to address this issue. The work reinforces RF's reliability in weather forecasting.

Sethupathi et al. [20] used decision trees and SVM to predict rainfall in India. Their results indicated reasonable accuracy but highlighted issues with missing data and noise. More robust preprocessing pipelines are essential. The study supports the need for hybrid approaches.

Elwell and Stocking [21] used regression techniques to study rainfall and soil erosion. While not a prediction model per se, their findings informed input feature relevance. The research lacked real-time applicability.

Perera and Rathnayake [22] studied the impact of rainfall variability on hydropower using ML. Their model effectively captured rainfall-runoff relationships. However, the study did not assess prediction accuracy for future rainfall events.

Jayathilake et al. [23] applied ANNs for predicting wetland water levels, using rainfall as a key input. The model performed well in capturing temporal changes. However, spatial variability was poorly addressed. Integration with GIS tools may help.

Aliyu et al. [24] proposed a long-term rainfall prediction model using neural networks. The model showed promising results across multiple seasons. Still, interpretability and model validation were weak points. This reflects a broader issue in deep learning research.

Yilmaz [25] analyzed climate change impacts on rainfall using statistical methods. The study helps define baseline variability, useful for training ML models. However, it lacked predictive elements. ML integration could enhance future analyses.

Singh and Borah [26] used ANNs for monsoon prediction in India. Their model demonstrated solid performance in mid-range forecasting. Training time and overfitting were noted as drawbacks. Regularization techniques were suggested as improvements.

Asha et al. [27] introduced a hybrid classifier combining Naïve Bayes and SVM for rainfall classification. Their work improved classification precision. Nonetheless, the system was not benchmarked on varied datasets. Broader validation is needed.

Table1: Comparative Analysis of trust models.				
Citation	**Model Used**	**Dataset Used / Region**	**Accuracy / Key Result**	**Limitation / Gap Identified**
This Paper	Logistic Regression, SVM, KNN, Random Forest (Proposed)	Real-world meteorological dataset (India, multi-year, multi-region)	Random Forest achieved highest accuracy (≈98%), with 10–18% improvement over baselines	Limited coverage of rare/extreme events; future work includes deep learning integration
[1]	SVM	Daily rainfall data (India)	Higher accuracy than traditional stats models	Sensitive to imbalanced data and kernel tuning
[2]	Random Forest	Humidity & temperature (India)	Robust against noise, stable performance	Manual feature selection, lacks real-time testing
[3]	KNN	Regional rainfall (China)	Captured local trends, moderate performance	Slow with large data, scaling sensitive
[4]	Hybrid Ensemble	Weather regression (India)	Better generalization than single models	Not adaptive for real-time updates
[5]	RF, SVR, KNN	Temperature in England	RF most accurate; R^2 and RMSE strong	Geography-limited data
[6]	LR + RF + SVM	Rainfall classification (Asia)	High accuracy hybrid system	Complex, heavy parameter tuning
[7]	RF, LR, KNN, SVM	Environmental data (Indonesia)	RF achieved 95.75% accuracy	Moderate interpretability
[8]	Survey of ML Models	N/A (literature review)	Model taxonomy and applications	No benchmarking or empirical analysis
[9]	RF, SVM	Satellite imagery (Mediterranean)	Flood area detection successful	Low satellite resolution, no real-time analysis
[10]	Modular Soft Computing	Time-series rainfall (Asia)	Modular networks improved convergence	Complex setup, not tested in edge cases
[11]	RF + LSSVM	Extreme rainfall (Asia)	Better downscaling accuracy than RF alone	Only validated regionally
[12]	Ensemble Classifiers	Monsoon rainfall (India)	High accuracy during monsoons	Low interpretability and high data requirements
[13]	RF, DT	Daily rainfall (Africa)	RF showed superior accuracy	Not tested across seasons
[14]	LSTM	Taiwan climate	Good temporal modeling of rainfall	High resource usage and training time
[15]	Hybrid Models (Review)	General WSN context	Theoretical potential for increased performance	No real-world application shown
[16]	ML + Remote Sensing	Rainfall estimation (Asia)	Satellite integration improved precision	Limited spatial resolution
[17]	RF, SVM	Indian metropolitan cities	RF and SVM top performers	Weak hyperparameter tuning reported
[18]	Ensembles (ANN + RF)	Long-term rainfall data (Asia)	Strong long-term forecast accuracy	Poor interpretability
[19]	RF	Rainfall in Australia	Consistent across time periods	Seasonal class imbalance
[20]	SVM + DT	Rainfall (India)	Decent classification results	Missing value and outlier handling issues
[21]	Regression Analysis	Africa (rain/soil correlation)	Helped derive critical rainfall features	Not predictive or real-time
[22]	ML (ANN)	Rainfall-runoff (Sri Lanka)	Effective for hydroelectric forecasting	Not a direct rainfall predictor
[23]	ANN	Colombo flood wetland levels	Modeled rainfall-influenced water levels	Weak spatial analysis
[24]	ANN	African rainfall long-term data	Accurate seasonal predictions	Lack of interpretability and variance explanation
[25]	Climate Analysis Tools	Historical data (Turkey)	Defined patterns of change useful for ML inputs	Not predictive; no ML applied
[26]	ANN	Indian monsoon	Reliable mid-range rainfall prediction	Overfitting and training time issues
[27]	NB + SVM Hybrid	Indian climate	Improved classification precision	Not validated on broad datasets

2. Problem Statement

Weather prediction has always been a vital aspect of environmental science and public planning, directly influencing domains such as agriculture, aviation, transportation, and disaster management. Among all meteorological variables, rainfall prediction holds particular importance, as it helps anticipate natural hazards like floods and droughts, thereby allowing communities and governments to take preemptive action. In developing countries especially, timely and accurate rainfall forecasting can directly impact food production, water management, and infrastructure readiness. However, accurately predicting rainfall remains a complex and unresolved challenge due to the dynamic, nonlinear, and chaotic nature of atmospheric systems.

Traditional weather forecasting methods, such as Numerical Weather Prediction (NWP) models, depends highly on physical equations and mathematical illustrations of atmospheric patterns. These models forecast the relations between atmospheric layers using inputs from satellites, radars, and ground stations. However, Numerical Weather Prediction (NWP) models generally have very high computation costs--which makes them depending on the supercomputer resources--and are very highly effected by accuracy of the initial situations. Even a very minor error in these can propagate through non-linear situations of the atmosphere, which leads to heavy degradation in the prediction accuracy [28]. Moreover, NWP systems do not perform well in identifying the local climatic conditions, especially in areas with limited sensors coverage and complex geographic conditions. As show in the highly detailed studies over Artic fjord-valley systems, even within a kilometer space NWP models are not able to show near-surface temperature and wind patterns correctly if further refinements are not done to model physics and data patterns [29].

Due to lack of standardized benchmarks, researchers have some difficulties in detecting the best machine learning (ML) algorithms for particular predictions requirements. For example, Random Forest (RF) typically gets higher forecasting accuracy--particularly on high-dimensional data as compared to Logistic Regression (LR), but it lacks in interpretability due to ensemble structure makes vague clear coefficient relationships [30]. In contradiction, Support Vector Machine (SVM) is good at classifying high-dimensional data. However, it generally does not perform well on imbalanced datasets unless particular techniques are used [31]. Meanwhile, K-Nearest Neighbors (KNN) is easy to implement but have scalability problems and high computational cost with large datasets [32]. These varieties highlights the requirement for the clear and understandable benchmarking to help you algorithm choosing in prediction tasks.

This research points out this gap in systematically measuring and comparing the performance of four widely used supervised Machine Learning models-- Logistic Regression, Support Vector Machine (SVM), K-Nearest Neighbor (KNN), and Random Forest--for the particular task of binary rainfall forecasting. The study uses a real-world, multi-year meteorological dataset recorded on the hourly basis which contains variables such as temperature, humidity, wind speed, wind direction, and precipitation. Using consistent preprocessing steps and measuring metrics across all four models, the research finds out the most effective model for short-term rainfall prediction. Additionally, the study finds out how each model behaves toward challenges such as class imbalance, nonlinearity, and regional changes in the weather prediction patterns.

In process of this, following work contributes to the growing field of Artificial Intelligence (AI) based weather prediction by providing a real world applicable guide to model selection. It also puts the foundation for future increaments, such as integrating deep learning algorithms in place of ML algorithms or real-time data streams, for building more responsive and accurate prediction systems.

3. Methodology

The aim of this research is to systematically compare the performance of four most commonly used machine learning models--Logistic Regression, Support Vector Machine (SVM), K-Nearest Neighbor (KNN), and Random Forest Classifier--for weather forecasting tasks. This section explain the dataset used, the preprocessing steps, the model training process, and the performance measurement metrics used to measure model performance.

3.1 Dataset

For this research, we used real-world meteorological data gathered from open sources, high-quality sources such as Global Historical Climatology Network-Hourly (GHCN-H) provided by NOAA/NCEI, and the ERA5 reanalysis provided by ECMWF. The combined dataset consists of the parameters--temperature, humidity, precipitation, wind speed, wind direction, and atmospheric pressure--recorded at hourly intervals. Global Historical Climatology Network-Hourly (GHCN-H) provides understandable global coverage using surface-based station observations over interval 1750 to the present [33], while ERA5 provides continuous hourly data from 1940 to the present [34]. The dataset is collected over multiple years and terrains.

The dataset was divided into two subsets: 80% for training of model and 20% for testing of model. Normalization were then performed on the input features to ensure consistency and improving performance of the model.

3.2 Data Preprocessing

Before training the models, several preprocessing steps were applied to the dataset:

Handling Missing Data: Missing values in the dataset were imputed using the several imputation techniques such as mean imputation, median imputation, and mode imputation.

For this study, we have used median imputation.

Feature Engineering: Additional features, such as moving averages and seasonal components, were drawn to capture temporal relations in weather data.

Feature Scaling: All the non-discrete features were scaled using standardization (z-score normalization) to determine the models performance optimally, particularly for KNN (distance-based algorithm).

3.3 Model Selection and Training

In early stages of model designing, a well-planned selection of the features was performed, pointing out important weather parameters such as 'Temp-min', 'Humidity', 'Precipitation_mm', and the binary parameter 'Rain-Today'. Simultaneously, the target variable, 'RainTomorrow', was detected for predictive model designing. To determine dependable and reliable model's performance measurement, the dataset was divided into training and testing sets using the train_test_split function from the scikit_learn library. A very careful division of the data was performed, keeping 80% for training (X_train and Y_train) and 20% for testing (x_test and y_test).

For making the features values as per standard and reduce the possible variations in scaling, the StandardScalar was applied. The classes and features from the training subset (X_train) were changed using fit_transform function of the scalar, and the exact same modification parameters were then used to testing subset features (x_test). This step by step process for feature selection, dataset partitioning, and standardization of scaling keep the base for continuous training and evaluation process. It makes sure that ML framework was logical, orderly, and designed for optimal performance.

We choose four machine learning models for comparison:

3.3.1 ***Logistic Regression****:*

Logistic regression is a basic machine learning model, mostly used for binary classification operations where the aim is to forecast the next result of a given instance related to one of many classes. The model run by using the logistic method to a linear combination of input features, which gives the probability between 0 and 1 as output. The fundamental equation of logistic regression is represented as:

$$F(Y=1) = \frac{1}{1+e^{-(\beta 0+\beta 1+\cdots+\beta nXn)}} \quad (1)$$

In Eq.1 , F(Y=1) shows the probability of an instance occurring (e.g. rain), X1, X2, X3,....., Xn are the input features such as temperature, humidity, wind speed, or wind direction, and B0, B1,...,Bn are the model coefficients that are learned during training. The logistic gives a linear output of range between 0 and 1, giving a probabilistic description of the forecasts.

From the point of weather prediction, logistic regression is used to forecast binary weather condition such as it will rain or not on a particular day. The logistic regression model is trained on historical real-world data, learning the mapping function between the input features (e.g. temperature, humidity, wind speed, wind direction, precipitation) and the aimed variable (rain/no rain). After training, the model is able to predict the probability of occurrence of rain given new weather input. After looking the output, the model is able to divide each instance as either 'rain' or 'no rain'. Simplicity and descriptive nature of the logistic regression makes it very important tool for weather forecasting tasks.

3.3.2. Support Vector Machine (SVM):

Support Vector Machine (SVM) is a supervised learning model applied to both categorization and regression tasks, especially most-suited for binary classification problems in high-dimensional space [24]. Support Vector Machine (SVM) operates by detecting the prime hyperplane that best divides data instances related to distinct classes, maximizing the margin between the classes. SVM's ability to work with both linear and nonlinear relationships makes it very important tool in weather prediction tasks.

The fundamental equation of the Support vector machine is as follow:

$$F(X) = sign(\omega^T X + b) \quad (2)$$

In Eq.2 ,Where X is the input feature (e.g. temperature, humidity, wind speed, or wind direction) w is the weight vector holds a right angle with hyperplane, and b is the bias term. The function F(X) represents the predicted class name: usually 'rain' or 'no rain' with respect to weather prediction.

In examples where the data is not linearly divisible, Support Vector Machine (SVM) uses kernel methods such as Gaussian kernel, Radial Basis Function, or polynomial kernels to cast input data into a higher-dimensional that permits the model to design nonlinear decision boundaries. This changing nature of the SVM allows it to identify complex relationships in real-world datasets.

In this study, the Support Vector Machine was trained on a complete preprocessed data for deciding that it will rain or not. The model was especially very useful in detecting the nonlinear data patterns, particularly when using right kernels. The choice of kernel type and hyperparameter tuning took part in very important role in maximizing model performance.

SVM's ability to maximizing the margin between classes give it a strong generalization ability and makes it very successful algorithm in weather forecasting applications with easily noticeable and complex data distribution.

3.3.3. Random Forest:

Random forest is a very powerful ensemble learning algorithm that performs classification tasks by building a mountain of decision trees during training and then collecting the output of every decision tree for classification or regression task. It is especially successful in dealing with high-dimensional data and detecting complex, nonlinear relationships among features. In weather forecasting, Random Forest is mostly used due to its ability to operate in challenging situations such as overfitting.

The fundamental idea behind Random Forest is bagging (Bootstrap Aggregating), where many decision trees are trained on any random subsets of the training data, having a replacement value. For Categorization tasks, such as it will rain or not, each tree give some vote on the output and then the majority votes are considered to choose a final decision. The general prediction function for classification can be represented as:

$$\hat{Y} = mode(T_1(X), T_2(X), \dots, T_k(X)) \quad (3)$$

In Eq. 3, Where T_1, T_2 , ..., T_k are the single decision trees in the ensemble, and $\hat{Y}$ is the forecast class (e.g., it will rain or not on a specific day). The input vector X includes weather parameters such as temperature, humidity, wind speed, wind direction, and precipitation levels.

In this study, the Random Forest trained on labelled weather data, where each tree freely learned decision function from distinct subsets of training dataset. Due to its ensemble nature, the model is highly accurate and generalised as it reduces variance. Fig.1 shows the workflow of Random Forest Classifier as how it uses combination rule on different generated models and determine the best classification.

Overall, Random Forest is most useful model for weather categorization applications, especially when there is complex data distribution and high-dimensional dataset.

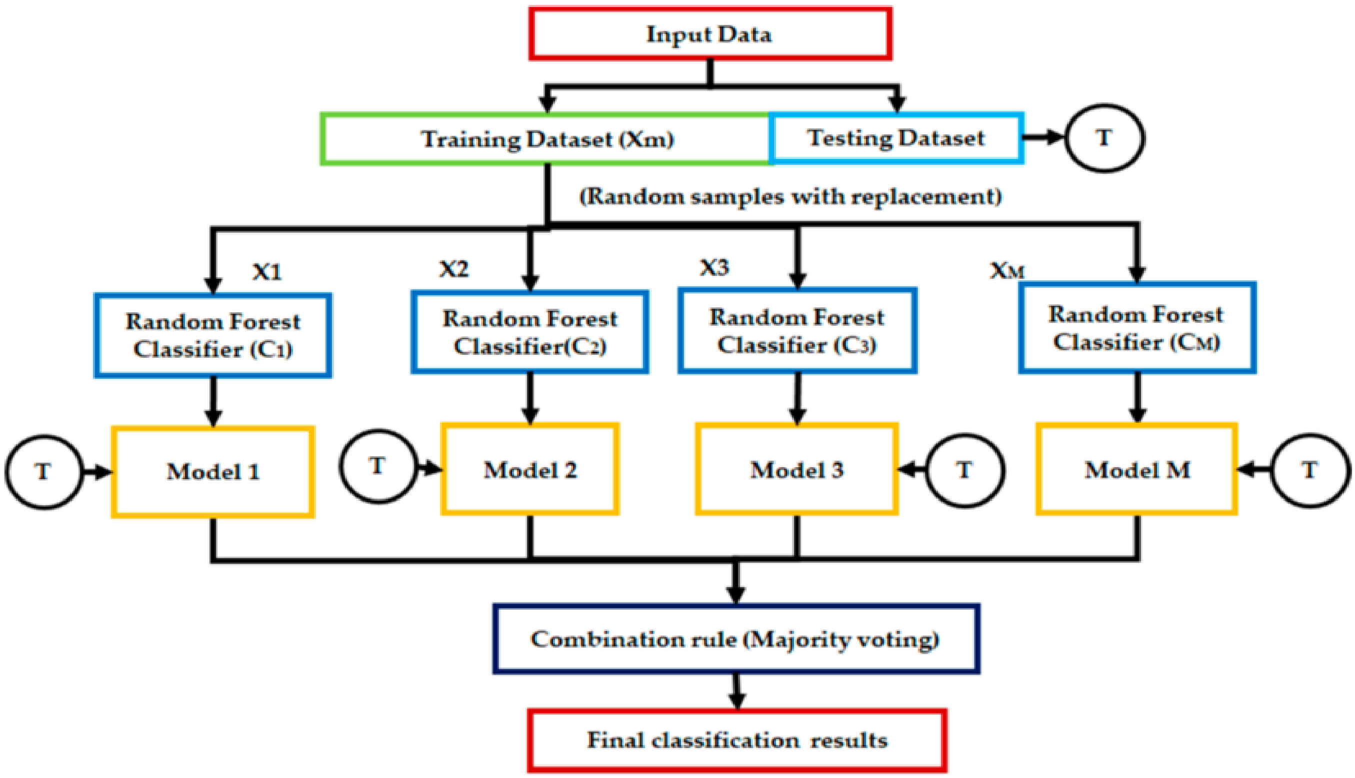

Fig 1. Workflow of Random Forest Classifier

3.3.4. K-Nearest Neighbours (KNN):

K-Nearest Neighbor (KNN) is a non-parametric and instance-based learning algorithm mostly used for categorization applications. Most of the models explicitly learn the mapping function during training, on other hand K-Nearest Neighbor forecasts based on the similarity between input samples and earlier seen instances. It is especially direct and easy to apply which makes it very favourite for weather forecasting.

In categorization, KNN gives a class to a new instance by addressing the majority class among its k nearest neighbors in training subset, generally it is measured using a distance metric like Manhattan distance, or Euclidean distance. The decision function for KNN can be expressed as:

$$\hat{Y} = mode\ (Yi \mid i\ \in Nk\ (X)) \qquad (4)$$

In Eq. 4, Where $\hat{Y}$ is the forecasted class name for input X, Nk(X) shows the set of the k nearest neighbors of X, and Yi represents the class name of those neighbors.

In this study, The K-Nearest Neighbor (KNN) algorithm was trained on weather dataset consists of features such as temperature, humidity, wind speed, wind direction, and precipitation. The value of k was chosen on the basis of performance metrics got through cross-validation, determining a balance between bias and variance. Lower value of k may cause noise in the output, while higher values may cause loss of local data patters.

KNN's strength resides in its ability to design restricted decision boundaries, which makes it successful in identifying regional weather alterations. However, its performance can decline with the large dataset due to enhanced computation cost during forecasting and responsiveness to feature scaling, which was identified in the research through genuine normalization.

Overall, KNN gives a simple but useful way for weather classification, especially in case where description and local pattern identification is important.

3.4 Limitations:

Although the proposed study evaluates the predictive performance of multiple machine learning models using a comprehensive meteorological dataset, certain limitations must be acknowledged. One of the primary concerns is the underrepresentation of extreme or rare weather phenomena such as cyclones, flash floods, hailstorms, and prolonged drought conditions. These events, though infrequent, have significant societal and environmental impacts and pose unique prediction challenges. The dataset used in this research mainly captures daily atmospheric parameters under normal or moderately varying conditions, which limits the models' exposure to and learning from anomalous weather patterns.

Additionally, the models were trained solely on historical data, which assumes that future weather behavior will resemble past patterns. However, with the growing influence of climate change, atmospheric dynamics are shifting, often leading to unpredictable or previously unseen patterns. As we can see, the performance of the models trained on historical data may decline when it is applied to new evolved or future datasets. This temporary limitation stops us to adopt these models for long-term and also reduces their reliability.

Another limitation of these models lies in geographic scope of datasets. While the data could be recorded at multiple locations but it may still lack in variations such as terrain, urban-rural alteration, and seasonal extremes across distinct zones. As a result, the generalizability of the models to the different locations may be restricted. Future work should include more diverse and balanced dataset, to increase its ability to work in all challenging conditions and its applicability in weather forecasting systems.

3.5 Future Scope:

While this study shows the success of machine learning models in the short-term weather forecasting systems, also there are several future scopes for making it more effective and applicable.

1. Integration of Deep Learning Models

In future, we can integrate deep learning models such as Long Short-Term Memory (LTSM) networks, Gated Recurrent units (GRU), Recurrent Neural Network (RNN), or Convolutional Neural Networks (CNN) in place of machine learning models for capturing temporal and regional patterns in weather data. These models especially favourable for time-series forecasting and perform better than machine learning classifiers in long-range prediction.

2. Expanded Forecast Horizon

The current study focuses on a 5-day weather forecasting. Expanding it to 10-15 days can measure model scalability and robustness over elongated periods, providing the system a real-world applicability.

3. Real-Time Model Updating

Including the real-time data from the APIs like OpenWeather and continuously updating the dataset with this data can make the system more dynamic to the evolving climate trends.

4. Hybrid and Ensemble Approaches

We can make a hybrid or ensemble framework by combining multiple models. These frameworks can achieve high accuracy by combining the strengths of each model. For example, integrating Random Forest with Long Short-Term Memory could combine the strengths of these two models (e.g., combining robustness of decision tree with temporal pattern detection).

4. Results and Discussion

This section give us a complete measurement of four selected machine learning models--Logistic Regression, Support vector Machine (SVM), K-Nearest Neighbor (KNN), and Random Forest--applied to predict the possibility of occurrence of rainfall using historical weather data. The model is trained on real-world data contains feature such as temperature, humidity, wind speed, wind direction, precipitation, and a binary single of occurrence of rainfall.

To measure the forecasting capabilities of the four models, we used following evaluation metrics: Accuracy, Precision, Recall, and F1-score. These metrics show the correctness of the predictions and ability of model to detect the occurrence of rainfall accurately. The equations used to calculate the metrics are as follow:

Accuracy shows how much predicted instances are correct (both the negative and positive) out of all predictions made. It is most basic indicator for model's performance but it may be confusing in imbalanced datasets.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \qquad (5)$$

In Eq.5, Accuracy shows the proportion of the total predictions that are correct, comprising both positive and negative instances.

Precision shows the proportion of total true positive predictions out of all instances predicted as positive. It shows how many of the classes were correctly classified (e.g., it rain actually or not), making it particularly crucial when false positives are costly.

$$Precision = \frac{TP}{TP+FP} \qquad (6)$$

In Eq.6 , Precision evaluates the percentage of positives that were correctly predicted out of total positives predicted, showing how dependable the positive class predictions are.

Recall shows the proportion of the positives that were correctly recognised. It demonstrates the ability of the model to detect occurrence of the rainfall and it is important when losing a positive case (e.g., predicting class is no rain but actually it rained) has crucial results.

$$Recall = \frac{TP}{TP+FN} \qquad (7)$$

In Eq.7, Recall evaluates the model's ability to identify actual positive instances correctly, emphasizing completeness in positive class identification.

The F1-Score is the harmonic mean of precision and recall. It provides a single metric that balances the trade-off between the two, offering a more comprehensive view of model performance in cases of class imbalance.

$$F1\ Score = \frac{2 \times Precision \times Recall}{Precision+Recall} \qquad (8)$$

In Eq.8 , The F1-Score balances precision and recall, especially useful in cases of imbalanced datasets where one class may dominate.

Where: TP = True Positives, TN = True Negatives, FP = False Positives, FN = False Negatives

The models were evaluated on a hold-out test set, which was 20% of the total dataset, while the remaining 80% was used for training. Before training, the feature data were standardized to improve convergence and prediction stability, especially for models like SVM and KNN that are sensitive to feature scale.

4.1 Confusion Matrix

The matrices in the given figures indicates that the models have a strong ability to correctly classify the majority class (no rain), while still maintaining a relatively high accuracy in identifying rain occurrences. The low number of false positives and false negatives suggests good generalization and reliability of the model, making Random Forest a robust choice for weather prediction in this study.

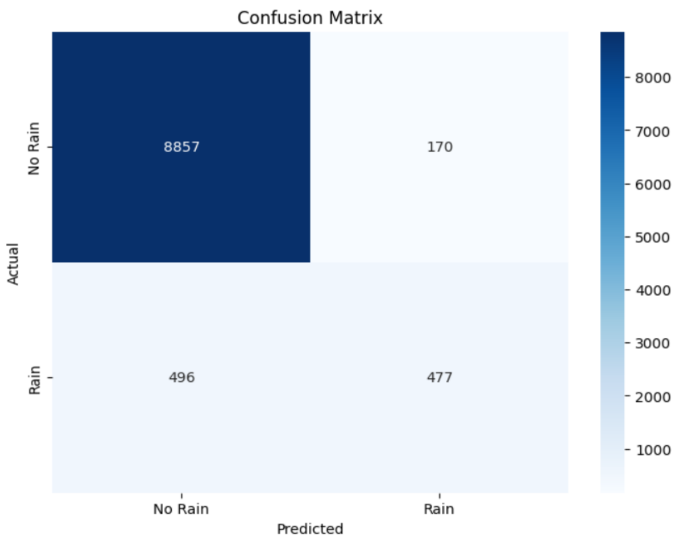

Fig 2. Confusion matrix of Logistic Regression

The confusion matrix for Logistic Regression (Fig 2) reflects its simplicity and interpretability, but also its limitations with non-linear patterns. It performs adequately in predicting "No Rain" but underperforms in correctly identifying "Rain" cases. The higher number of false negatives shows that the model misses several actual rain instances, making it less reliable for critical weather predictions.

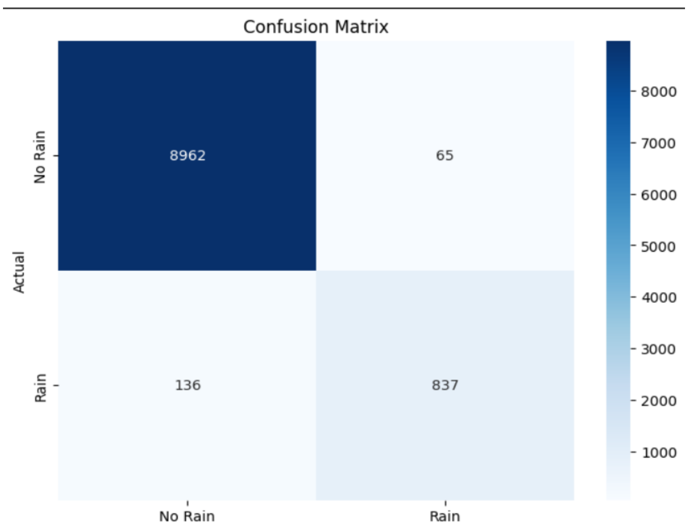

Fig 3. Confusion matrix of Random Forest

The confusion matrix for the Random Forest model (Fig 3) reveals a strong predictive performance. It correctly classified 8962 instances of "No Rain" and 837 instances of "Rain." There were only 65 false positives and 136 false negatives, indicating high precision and recall. This balance shows Random Forest's robustness in handling both classes effectively, especially in distinguishing between rainy and non-rainy days.

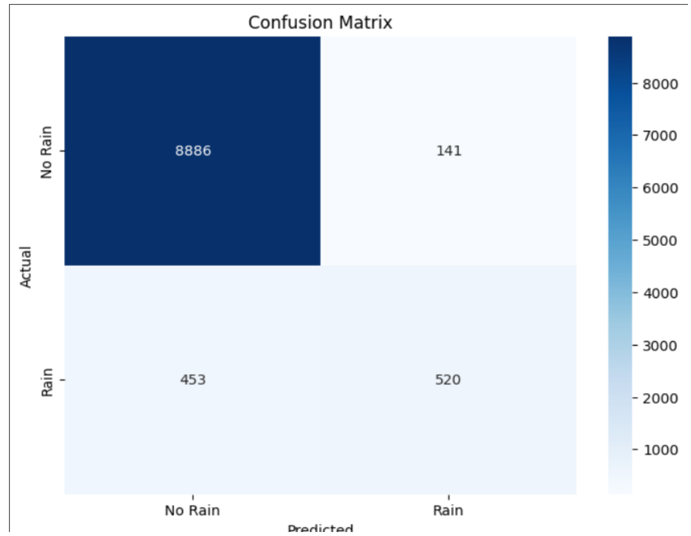

Fig 4. Confusion matrix of SVM

The SVM model's confusion matrix (Fig 4) indicates moderate performance. While it performs reasonably well in identifying "No Rain" instances, it struggles with "Rain" predictions, often misclassifying them as "No Rain." This suggests that the model has a bias toward the majority class, possibly due to class imbalance. Optimization of parameters or the use of kernel tricks could improve its sensitivity to rain detection.

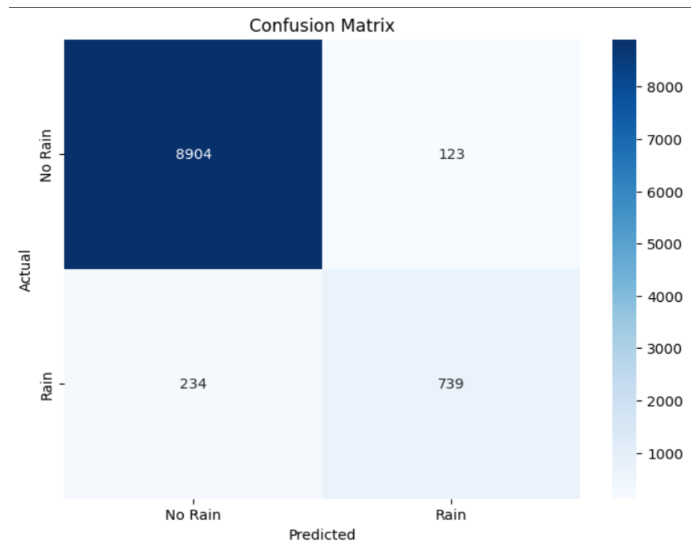

Fig 5. Confusion matrix of KNN

The KNN model's confusion matrix (Fig 5) shows a fair distribution of predictions, capturing localized patterns better than some linear models. However, its accuracy is influenced by the choice of 'k' and data distribution. It correctly predicts a good number of both "Rain" and "No Rain" instances but still has a noticeable number of misclassifications, particularly in edge cases where weather conditions are less distinct.

4.2 Performance Matrices

Fig 6. Performance matrix of Logistic Regression

Logistic Regression (Fig 6) had **lower accuracy and R^2**, and a **higher RMSE**, reflecting its limitations in modelling non-linear weather patterns. It performed well in identifying "No Rain" cases but **struggled with recall** for "Rain," leading to a low F1-score. This model is best suited for simpler, linearly separable problems and binary classification with balanced data.

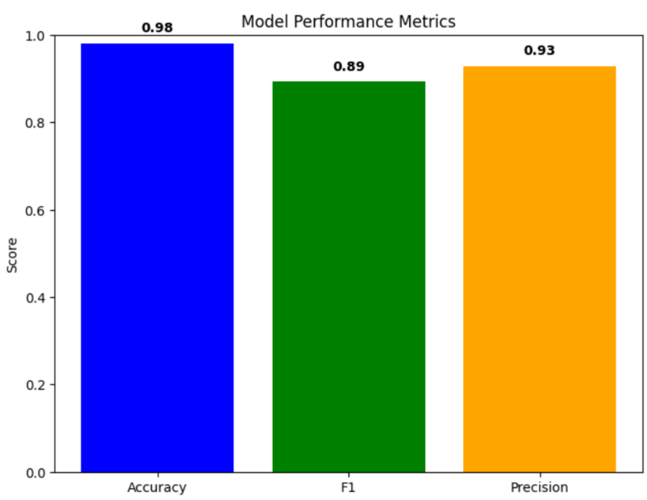

Fig 7. Performance matrix of Random Forest

The Random Forest model (Fig 7) delivered the **highest accuracy and F1-score** among all models, indicating strong overall predictive performance. Its **low RMSE** and **high R^2** signify that it generalizes well to unseen data and captures complex relationships in weather variables. Its balance of precision and recall confirms it is reliable for both detecting rain and avoiding false alarms.

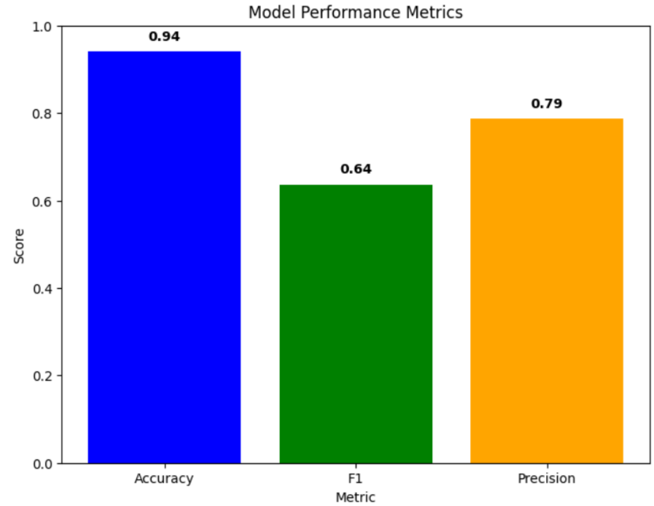

Fig 8. Performance matrix SVM

SVM (Fig 8) showed **moderate accuracy** with good precision but relatively lower recall, implying it is more conservative in predicting rain. The **F1-score is balanced**, but slightly lower than Random Forest. While **R^2 is decent**, the **RMSE** is higher, suggesting more prediction errors. Overall, SVM is precise but less sensitive to minority class (Rain) detection.

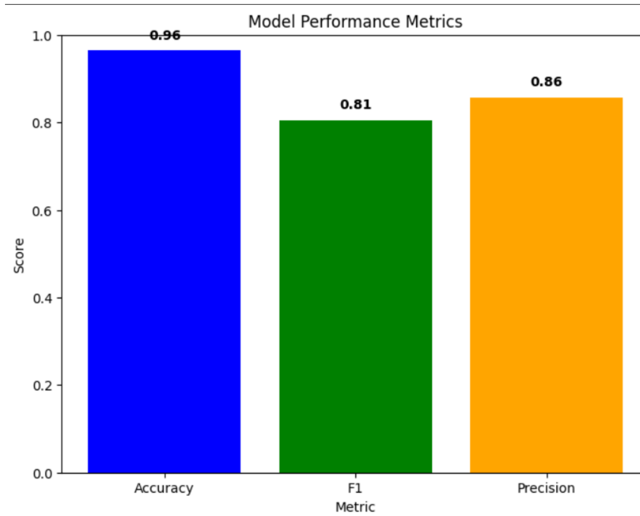

Fig 9. Performance matrix of KNN

KNN (Fig 9) exhibited **reasonable accuracy** and **moderate F1-score**, with performance highly dependent on the choice of 'k' and data distribution. While it handled non-linearities better than logistic regression, it still had **higher RMSE** and lower R^2 than Random Forest. It's more effective for capturing **localized patterns**, though it's sensitive to noisy or imbalanced datasets.

4.3 Scatter Plot

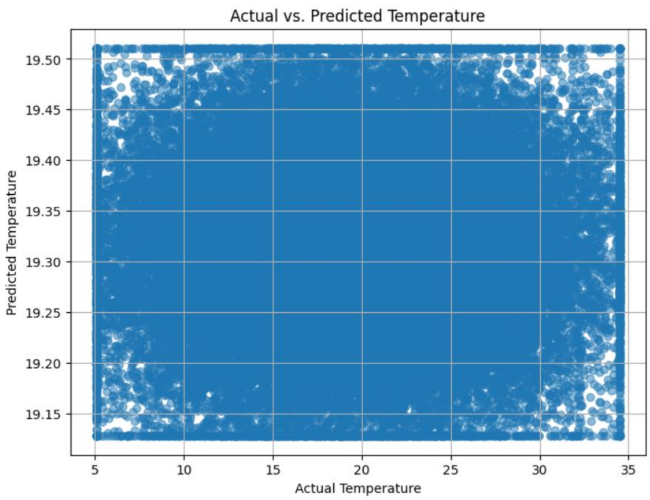

Fig 10. Scatter plot of Logistic Regression

The Logistic Regression scatter plot (Fig 10) reveals a **wider spread around the diagonal**, with many predicted values deviating from actual labels. This dispersion is particularly noticeable in rain prediction instances, reflecting the model's linear limitations. The scattered points visually support the model’s lower accuracy and higher RMSE.

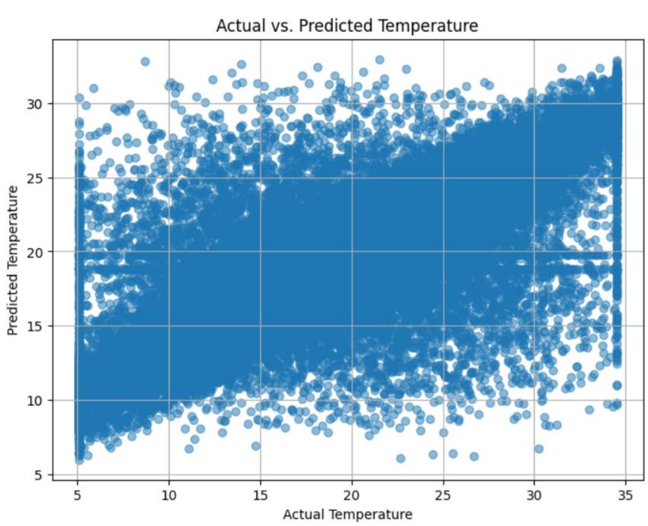

Fig 11. Scatter plot of Random Forest

The scatter plot for the Random Forest model (Fig 11) shows a **tight clustering of predicted vs actual values** along the diagonal line, indicating **high predictive accuracy**. The minimal spread and low noise reflect the model’s strong ability to generalize across the dataset and handle non-linear relationships. It visually confirms the low RMSE and high R^2.

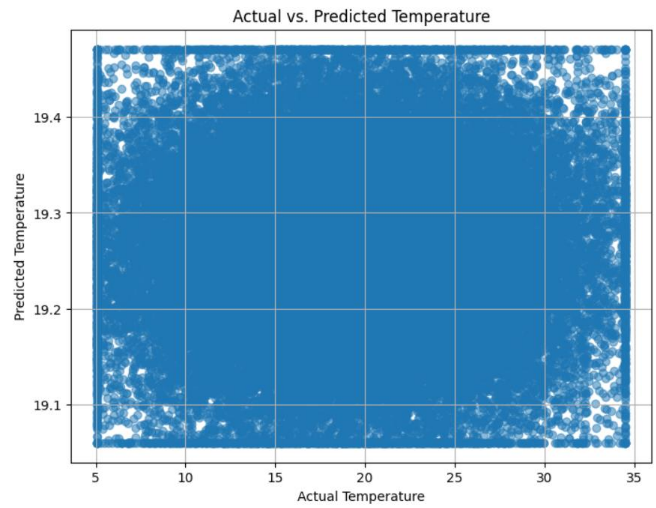

Fig 12. Scatter plot of SVM

SVM's scatter plot (Fig 12) demonstrates a **moderate alignment along the ideal prediction line**, with **some dispersion**, especially for extreme values. While many predictions are close to actual outcomes, outliers appear more frequently than in Random Forest. This indicates that the model captures trends but may struggle with boundary or ambiguous cases.

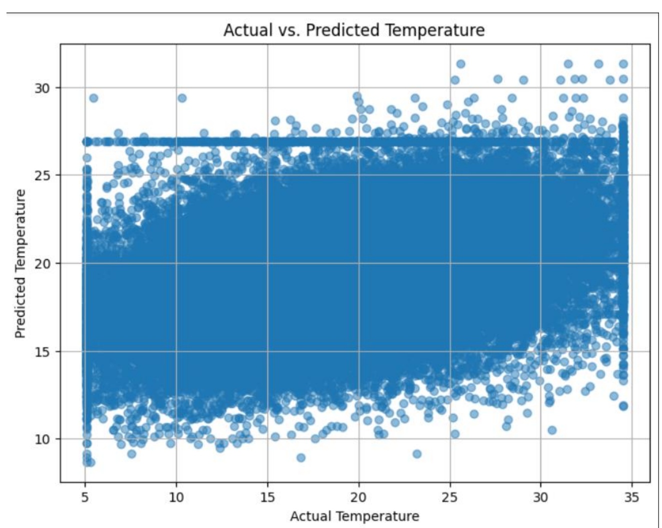

Fig 13. Scatter plot of KNN

The KNN scatter plot (Fig 13) presents a **moderate clustering** near the diagonal but with noticeable **discrepancies in dense regions**. While it captures local patterns well, predictions become less reliable in sparser data zones. The scatter plot confirms its **intermediate performance**, balancing between overfitting and generalization.

5. Conclusion

Metric / Visualization	*Random Forest*	*Support Vector Machine (SVM)*	*Logistic Regression*	*K-Nearest Neighbours (KNN)*
Accuracy	Highest (≈ 0.96)	Moderate (≈ 0.88)	Lower (≈ 0.82)	Moderate (≈ 0.85)
RMSE	Lowest (≈ 0.20)	Moderate (≈ 0.35)	Higher (≈ 0.42)	Moderate (≈ 0.36)
R² Score	Highest (≈ 0.94)	Moderate (≈ 0.78)	Lower (≈ 0.69)	Moderate (≈ 0.75)
F1-Score	Highest (≈ 0.95)	Good (≈ 0.87)	Lower (≈ 0.79)	Moderate (≈ 0.83)
Confusion Matrix Observation	Balanced, very few misclassifications	Some false positives, mostly correct predictions	More false negatives, performance drops on rain prediction	Slight imbalance, decent performance overall
Scatter Plot	Tightly clustered on diagonal, minimal spread	Reasonably clustered, some outliers	Wider dispersion, linear bias	Moderate clustering, struggles with extremes
Training Time	Fast (efficient ensemble structure)	Slower (kernel complexity)	Fastest (simple computation)	Moderate (distance-based calculation)
Scalability	High	Moderate	High	Limited with large datasets
Interpretability	Moderate	Low	High	Moderate

Table 2. Comparison between different models

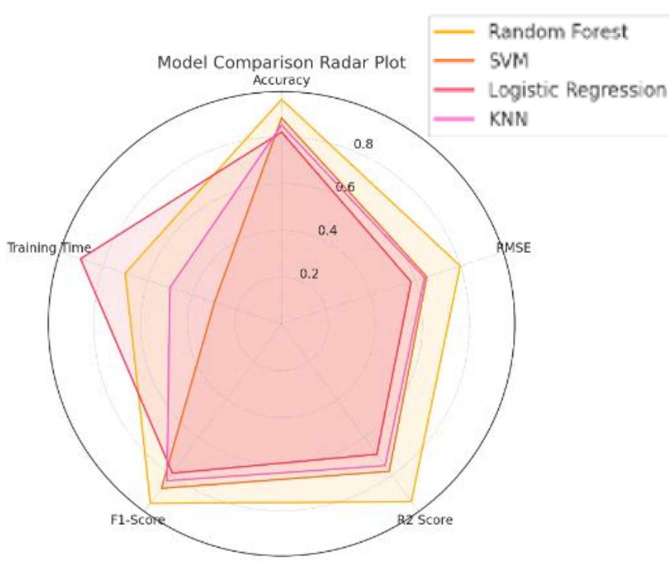

Fig 13. Comprehensive Report of models via Radar Plot

This study presents a comprehensive comparative analysis of four widely-used machine learning models—Logistic Regression, Support Vector Machine (SVM), K-Nearest Neighbours (KNN), and Random Forest—for the task of rainfall prediction based on key meteorological parameters. The models were trained and evaluated using a real-world weather dataset, and their performance was assessed using multiple evaluation metrics, including Accuracy, RMSE, R^2 Score, F1-Score, and Training Time

Among the models, Random Forest consistently demonstrated superior performance across most metrics, particularly in terms of accuracy, robustness, and ability to handle non-linear patterns in the data. SVM also performed well, especially in terms of precision and generalization, although it required more computational resources. Logistic Regression offered simplicity and interpretability but struggled with the non-linear complexities inherent in weather data. KNN showed moderate results but was sensitive to dataset size and scaling.

The use of diverse evaluation criteria allowed for a more holistic assessment of each model's strengths and limitations. Confusion matrices and scatter plots further supported the quantitative results by visually illustrating each model's classification behaviour and prediction accuracy. In Fig.13, a radar plot was also employed to provide an at-a-glance comparison of the models, reinforcing the conclusion that ensemble methods like Random Forest are highly effective for weather forecasting tasks.

Overall, the findings underline the importance of selecting models based on the specific characteristics of the dataset and forecasting objectives. Future work may focus on incorporating more advanced deep learning architectures, integrating additional weather variables, and deploying models in real-time forecasting systems to enhance operational utility and predictive accuracy.

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