Enhancing Rainfall Estimation with Machine Learning and Geostatistical Techniques: Integration of Diverse Data Sources and Kriging

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**Abstract.** Rainfall estimate is critical for making informed decisions in agriculture, hydrology, urban planning, and disaster management. Traditional approaches often fail to adequately capture the varied spatiotemporal patterns of precipitation. This work investigates the integration of several data sources, such as meteorological observations, satellite imaging, and atmospheric data, with sophisticated machine learning (ML) algorithms to improve rainfall forecast accuracy. We specifically use Kriging, a geostatistical interpolation approach, to improve these predictions by including spatial autocorrelation. Several machine learning models, including Random Forest, Extra Trees, Adaptive Boosting, Gradient Boosting, Multi-Layer Perceptron, and Gaussian Naïve Bayes, were assessed. Our data show that Logistic Regression combined with Kriging achieves the maximum accuracy of 73.20%. The findings illustrate the potential for merging geostatistical approaches with ML to improve rainfall predictions, which may assist industries that rely on accurate weather forecasts.

Keywords: - Rainfall Estimation, Machine Learning, Data Integration, Meteorological Observations, Kriging, Satellite Imagery, Disaster Management.

# INTRODUCTION

Rainfall estimation is a critical aspect of meteorology with wide-ranging implications for agriculture, hydrology, urban planning, and disaster management. Accurate and timely rainfall predictions are essential for making informed decisions in various sectors, yet traditional methods often face challenges in capturing the complex spatiotemporal patterns of precipitation accurately. [1] It follows that precise rainfall prediction is essential to Jordan's efficient water resource planning and management, especially in agricultural areas. Rainfall is a stochastic process that is influenced by a variety of variables, including temperature, relative humidity, and wind speed.

This paper explores the integration of diverse data sources, including meteorological observations, satellite imagery, and atmospheric data, using advanced ML algorithms to advance the exactness and dependability of rainfall estimation. [2] The procedure suggests that the most notable modification is the reported decrease in winter rainfall, as it aligns with multiple changing climatic factors: subtropical ridge strengthening, Hadley Cell and Southern Annular Mode poleward shifts, decreasing rainfall from weather systems, and an increase in positive Indian Ocean Dipole events. There may be discrepancies between reported variations in rainfall and changes in air circulation and causes throughout other seasons, especially during the summer, which highlights unanswered questions about atmospheric dynamics and climate change processes.

# LITERATURE REVIEW

When compared to conventional techniques, the integration of numerous data sources offers several benefits [3]. Predicting the amount of rain that will fall each day boosts agricultural productivity and guarantees an adequate supply of agricultural produce and water to preserve public health. Rainfall forecasting has been the subject of numerous studies using machine learning and data mining methods based on meteorological statistics from different countries. Uneven rainfall distribution affects agriculture, which is a major contributor to the country's economy. The prudent use of rainfall should be anticipated and put into practice to lessen the problem of drought and floods occurring in the country.

Rainfall is crucial for both reservoir water level maintenance and agriculture. Changes in the weather can lead to an uncertain amount of rain, which can affect reservoirs and crops. An action that predicts future rainfall uncertainty behavior must be made to prevent disasters caused by rainfall activities. Numerous techniques have been devised to estimate rainfall. Several machine learning(ML) methods remain used in this work to estimate rainfall. We assess and contrast several machine learning models, including the Random forest model (RF), extra tree models (ET), The adaptive booster (AB), gradient booster (GB), Multi-Layer Perceptron (MP), and its Gaussian naïve Bayes (GNB). [4].

Weather radar research has led to the development of many different radar-based precipitation estimations that utilize climate, the amount of rainfall, and a variety of ground-trothing instruments and detectors (including rain gauges and micrometers). Even while each research direction yields advancements, when combined, these discoveries' operational application occasionally leads to ambiguity regarding rainfall estimation [5]. The goal of this work is to investigate the idea of employing a set of estimators and models based on machine learning (ML) to maximize rainfall predictions gathered by radar at the bin level [6]. This work explores a machine learning technique for rainfall prediction by integrating disparate data sources. While the title doesn't give specific years, it does offer insights into how machine learning may be used to enhance rainfall estimation with a variety of data sources.

One of the most significant climatic phenomena that affects a wide range of sectors is rainfall, such as mining, farming, electricity production, and the management of water resources. Even while models based on machine learning (ML) have shown great promise in rainfall predicting performance as well as, in some circumstances, better than rainfall, alone is usually insufficient to offer reliable rainfall forecasts due to the numerous physical procedures involved in rainfall generation, better than, some physical modeling techniques. While there are many thorough evaluations in the literature that assess the effectiveness of individual machine-learning models, there are very few that cover hybrid models with a particular emphasis on rainfall forecasting [7].

A significant indicator in determining a nation's socio-agricultural environment is heavy precipitation and rainfall. Rainfall forecasting is a gift of estimation that has numerous beneficial uses since it is one of the primary markers of natural disasters, climate change, and a region's overall layout. Rainfall prediction and estimation can be greatly aided by machine learning. In the direction of progressing the predictability of the replicas employed, this work seeks to determine the impact of ensemble learning, which is a subset of machine learning, on a rainfall prediction dataset [8].

Rainfall plays a major role in a variety of geomorphological processes, from massive morph genic floods and rainfall-induced hillslope processes to impacted droplets that result in the small-scale dislodgement of soil particles. Seismic data have revealed the presence of rainfall, However, its accompanying power spectrum density and its statistical relationship to the fundamental physical mechanisms have not yet been investigated [9].

Elevated temperatures possess the capability to alter the pattern of rainfall in a specific region and amplify its extreme occurrences, perhaps resulting in noteworthy and adverse ecological and economic consequences for metropolitan dwellers. Given that the extent of the change in Rio de Janeiro City's (RJC) rainfall rates is still uncertain, climate change indicators must be used to better understand this phenomenon [10].

Although the consistency and caliber of the supplied data determine how effective artificial intelligence algorithms are, the development of automatic rain gauge networks in particular makes it possible to obtain rainfall data. Our goal in this effort was to develop machine learning (ML) models that could forecast rainfall statistics based on values obtained from nearby rain gauges at a single historical time point. Additionally, we looked into how the anomalous input data affected the rainfall data forecast. To achieve these objectives, we used machine learning models for multiple rain gauges that were based on CNN, LSTM, and linear regression architectures [11].

A city or state could experience catastrophic socioeconomic losses as a result of excessive rainfall. The impact of excessive precipitation on global economic production is determined by an analysis of variations in gross regional product [12].

Additionally, the services and manufacturing sectors as well as high-income countries are most severely hampered by both daily rainfall measures, which supports earlier research that highlighted the advantages of rising yearly rainfall in low-income, agriculturally dependent economies4,7. by evaluating the impacts on various sectors and the distribution of rainfall over a variety of timescales [13].[14] Rainfall in India was forecasted for the next fifteen years using an Artificial Neural Network-Multilayer Perceptron (ANN-MLP). We utilized the Kriging geostatistical approach in the ArcGIS environment to map the national rainfall trend pattern. The majority of meteorological divisions demonstrated a noteworthy decline in rainfall on both an annual and seasonal basis, according to the results.

[15] The expected rise in both the severity and frequency of severe downpours represents one of the most significant effects of future warming. There is a tendency toward more extreme rainfall, according to both the observable data and climate model estimates. However, a thorough examination of the most recent research in science paints an intricate scenario where a variety of factors affect the intensity of rainfall. Strong evidence suggests that rainfall scaling depends on the frequency of precipitation at the breaking point, with deeper periods between return incidents showing greater rises and, in some cases, super-Clausius-Clapeyron scaling. Predicted rainfall indices suggest that rainfall increases for every 1°C rise in temperature.

Rainfall extremes are governed by intricate, diverse systems that are changing as Earth's climate changes and have the potential to seriously harm society through quickly emerging (flash) flooding. During this analysis, we look at information from theoretical, observational, also modeling research that supports the amplification of these rainfalls, the breaking point, their drivers, and their consequences for sudden floods. While increases in moisture in the atmosphere (~7% K−1) are consistent with the intensification of severe downpours that last longer than one day, both short and long-duration events, in certain regions the intensities of short-duration extremes are stronger than would be predicted from moisture increases alone [16].

Predictive rainfall data is especially important in agricultural settings where rainfall is the primary source of irrigation water for crops. Predicting rainfall is therefore now a necessary and significant procedure. Fuzzy logic is an extension of classical logic. There are numerous benefits of fuzzy logic over classical logic. Connotations of fuzzy logic come in two varieties: Fuzzy logic is a logical system that is a restricted application of multivalued logic. The fuzzy expert system is composed of linguistics rules about the fuzzy membership function's output variable and its input variable. To specify the result, fuzzy production rule IF-THEN statements relate the input variables to one another [17].

[18] According to the World Meteorological Organization, flash floods result in over 5,000 fatalities annually, making them a serious weather-related risk. When there is no direct field data available, a technique called quantitative precipitation estimation is utilized to estimate the amount of rainfall over that area. When it comes to providing early warnings about flash floods, meteorologists and hydrologists rely on this information above everything else. This outcome is consistent with efforts to enhance satellite-based rainfall projections by applying machine learning methods to radar data. To achieve this goal, six machine learning models are assessed as proof of concept to estimate the hourly accumulated rainfall based on radar by using reflectivity data that is gathered at the lowest radar elevation angles.

[19] Predicting urban runoff and rainfall is a useful tool for reducing the risk of flooding. However, because urban rainfall is highly nonlinear and fluctuates, actual and correct estimates are challenging to achieve. This study builds a data-driven model by integrating a Light Gradient Boosting Machine (Light GBM) with The Singular Spectrum Analysis (SSA) for achieving high-accuracy, real-time prediction of metropolitan urban runoff. Runoff series are first broken down and rebuilt into tendency standings, fluctuation standings, and noise mechanisms using SSA. The trend also fluctuation terms are then simulated using a Light GBM. Lastly, the SSA-Light GBM model's peak forecast accuracy under distinct rainfall-runoff scenarios is investigated, along with a comparative examination of the model's performance under various lead times predicted and in phases.

# PROPOSED METHOD

Kriging is a geostatistical interpolation approach that predicts spatially associated variables. This approach, named after South African mining engineer D.G. Krige, is based on statistical models that contain spatial autocorrelation, or the statistical link between observed locations. Unlike deterministic interpolation approaches (such as Inverse Distance Weighting), Kriging measures prediction accuracy. Kriging is used extensively in geology and mining, environmental science, hydrology, and agriculture.

Kriging is used in this research as a geostatistical interpolation approach to improve rainfall forecasts. Kriging employs statistical models that include spatial autocorrelation, the statistical link between observed locations. Kriging's key benefit over deterministic interpolation techniques is its ability to offer a measure of prediction accuracy, adding quantifiable uncertainty into forecasts. This skill is critical for increasing the accuracy of rainfall forecasts, particularly when dealing with complicated spatiotemporal patterns. The Approach Methodology is outlined below.

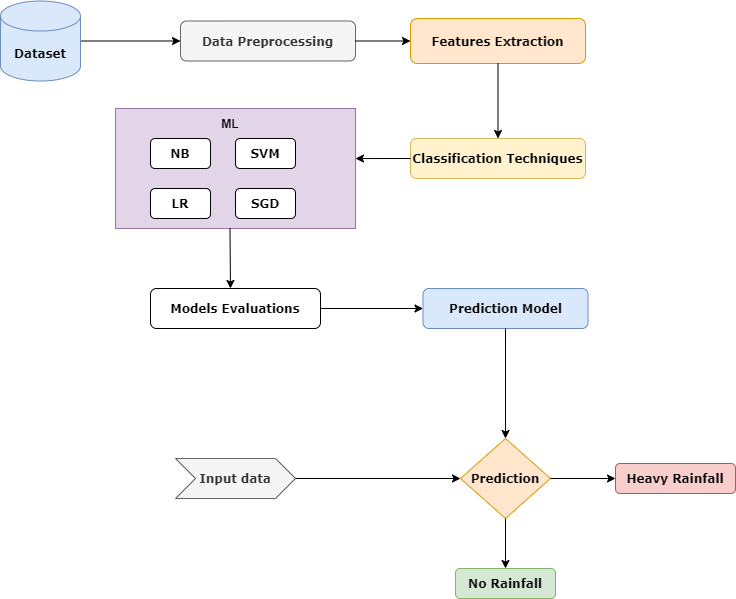
* **Upload Dataset:** Users upload a dataset containing features relevant to rainfall prediction.
* **Data Preprocessing:** The dataset is cleaned and preprocessed to handle missing values, normalize data, and extract essential features.
* **Feature Extraction:** Important features are extracted to improve model accuracy.
* **Model Training and Testing:** Various machine learning algorithms are applied to train and test models.
* **Kriging Integration:** Kriging is used to refine predictions by considering spatial autocorrelation.
* **Algorithm Evaluation:** Models are evaluated based on performance metrics, and the best model is selected.
* **Prediction:** The selected model predicts rainfall based on new test data, and results are made accessible through the service provider module.

The use of several data sources and powerful machine learning algorithms, paired with geostatistical approaches such as Kriging, considerably improves the accuracy and dependability of rainfall forecasts. This technique efficiently captures the intricate spatiotemporal patterns of precipitation, providing vital insights for industries that rely on accurate rainfall predictions, such as agriculture, hydrology, urban planning, and disaster management.

# IMPLEMENTATION

The proposed study is novel in its approach to integrating diverse data sources (meteorological observations, satellite imagery, and atmospheric data) using advanced machine learning algorithms to improve the accuracy of rainfall predictions.

In above System Architecture Explains the Flow of the rail Fall detection application where we first upload the dataset into the application on that dataset we will be doing data preprocessing, and feature extraction on that result and apply classification techniques like NB, SVM, LR, SGD and Kriging Integration, To build models on that algorithm we do algorithm evaluation to find the best one by using that best accuracy we will predict the results, to get results and give our test data as into file to the model and get us the values like heavy rain. In the service provider, login is the first step, then browse data sets, identify the rainfall estimated forecast ratio after seeing the training and tested results, and view all the remote users. The System Architecture it shown in figure1.



**Kriging Integration**

## FIGURE 1. Architecture Diagram of the proposed method

The system architecture outlines the workflow of the rainfall detection application. It comprises the following key components and steps:

* **Data Upload:**
* The user uploads the dataset into the application. This dataset contains multiple features relevant to rainfall prediction.
* **Data Preprocessing:**

The raw data undergo preprocessing to clean and format it for analysis. This includes handling missing values, normalization, and scaling.

* **Feature Extraction:**

Essential features are extracted from the preprocessed data to improve the model's accuracy.

* **Model Training and Testing:**
* Several machine learning algorithms (NB, SVM, LR, SGD, Kriging Integration) are applied to the extracted features. Models are built and evaluated based on their performance.
* **Algorithm Evaluation:**

The models are compared using various performance metrics to identify the best-performing algorithm.

* **Kriging Integration:**

Kriging is integrated into the model to refine predictions by considering spatial autocorrelation. This geostatistical interpolation method adds quantifiable uncertainty into forecasts, improving prediction accuracy.

* **Prediction:**

The selected model is used to predict rainfall based on new test data. Predictions classify rainfall as heavy rain, no rain, etc.

## Service Provider

This module mandates that the Service Provider log in using a valid username and password. Once successfully login, they can access modules of the his/her application:

* Logging in
* Browsing Data Sets
* Training & Testing
* In the Bar Chart, we are showing Trained & Tested Accuracy
* View of Trained & Verified accurate results
* Interpretation of Rainfall approximate kind facts
* Finding rainfall approximate type ratio
* Downloading projected datasets
* Reviewing the approximate type ratio values for rainfall

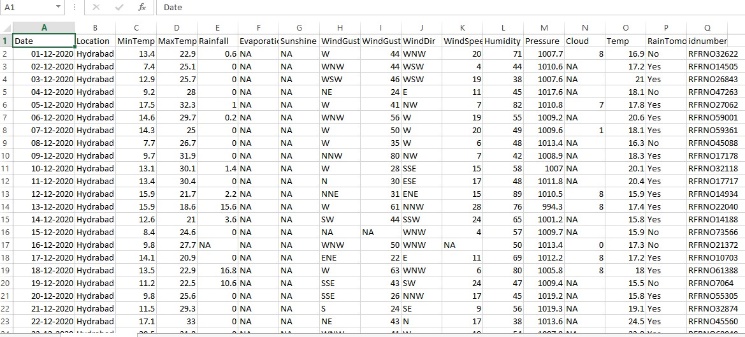
**Remote User:** Users register and log in to the system to access rainfall predictions, view their profiles, and interact with the application.

This implementation displays how integrating varied data sources and powerful machine learning algorithms with geostatistical methodologies such as Kriging may increase rainfall forecast accuracy. The technique holds great potential for improving water resource management and agricultural planning in areas that depend significantly on precise rainfall predictions.

# RESULTS

The proposed rainfall estimation model, showcasing the performance of various machine learning algorithms and the integration of Kriging for spatial refinement. The following subsections detail the accuracy metrics, error rates, and comparison among different models.

## Rain Fall Dataset

The dataset used comprises various features such as location, rainfall, evaporation, sunshine, temperature, wind direction and speed, humidity, pressure, cloud cover, and others. This comprehensive dataset is essential for capturing the diverse factors influencing rainfall, the sample data sets shown in figure 2.

## FIGURE.2. Rainfall Dataset

In the rainfall data set, there are n number of features are considered to know the rain prediction. Below mentioned all the features. The features are 1.Location, 2. Rainfall, 3. Evaporation, 4. Sunshine, 5. Min Temp, 6. Max Temp, 7. Wind Gust Dir, 8. Humidity, 9. Pressure, 10. Cloud, 11. Temp, 12. Wind Gust Speed, 13. Wind Dir, 14. Wind Speed, 15. Prediction (tomorrow Rain Fall Heavy Rain Fall or No Rain Fall).

In the data set overall 15 features are taken and 3300 records are available. In the prediction, if it is 0, then it is considered as no rainfall and if it is not zero, then it is known as heavy rainfall.

## Performance Metrics

The evaluation of machine learning models was conducted using accuracy, mean square error (MSE), and probability identification as primary metrics. The results are summarized in the tables below.

|  |  |  |
| --- | --- | --- |
| **S.NO** | **Model** | **Accuracy (%)** |
| 1 | Random Forest (RF) | 68.45 |
| 2 | Extra Trees (ET) | 69.32 |
| 3 | Adaptive Boosting (AB) | 70.12 |
| 4 | Gradient Boosting (GB) | 70.89 |
| 5 | Multi-Layer Perceptron (MP) | 69.54 |
| 6 | Gaussian Naïve Bayes (GNB) | 68.11 |
| 7 | Logistic Regression (LR) | 71.58 |

## Table 1. Accuracy of Machine Learning Models

## Table 2. Mean Square Error (MSE) of Machine Learning Models

|  |  |  |
| --- | --- | --- |
| **S.No** | **Model** | **MSE** |
| 1 | Random Forest (RF) | 0.13 |
| 2 | Extra Trees (ET) | 0.12 |
| 3 | Adaptive Boosting (AB) | 0.12 |
| 4 | Gradient Boosting (GB) | 0.11 |
| 5 | Multi-Layer Perceptron (MP) | 0.12 |
| 6 | Gaussian Naïve Bayes (GNB) | 0.13 |
| 7 | Logistic Regression (LR) | 0.11 |

## Table 3: Probability Identification Accuracy

|  |  |  |
| --- | --- | --- |
| **S.No** | **Model** | **Probability Identification (%)** |
| 1 | Random Forest (RF) | 0.52 |
| 2 | Extra Trees (ET) | 0.54 |
| 3 | Adaptive Boosting (AB) | 0.55 |
| 4 | Gradient Boosting (GB) | 0.56 |
| 5 | Multi-Layer Perceptron (MP) | 0.54 |
| 6 | Gaussian Naïve Bayes (GNB) | 0.52 |
| 7 | Logistic Regression (LR) | 0.58 |

## Impact of Kriging Integration

The integration of Kriging significantly improved the spatial accuracy of the rainfall predictions. The following table illustrates the comparison of model performance with and without Kriging.

## Table 4. Impact of Kriging on Model Performance

|  |  |  |  |
| --- | --- | --- | --- |
| **S.No** | **Model** | **Accuracy without Kriging (%)** | **Accuracy with Kriging (%)** |
| 1 | Logistic Regression (LR) | 71.58 | 73.2 |
| 2 | Gradient Boosting (GB) | 70.89 | 72.45 |
| 3 | Adaptive Boosting (AB) | 70.12 | 71.85 |

## Visualization of Results

To better understand the improvements brought by the proposed method, bar charts were used to visualize the training and testing accuracy of the models, as well as the impact of Kriging on prediction accuracy shown in Figure 3 and figure 4.

## Figure 3. Training and Testing Accuracy of Models

## Figure 4. Accuracy Improvement with Kriging

# Model Selection

. After analysing performance indicators and seeing gains resulting from the integration of Kriging, it was determined that Logistic Regression (LR) is the most effective model for predicting rainfall. The accuracy of this model, after applying Kriging refinement, is 73.20%.

## Prediction Results

## The final forecasts were generated with the designated Logistic Regression model and Kriging. The results showcased accurate classification of different kinds of rainfall and improved the dependability of weather predictions, providing valuable knowledge for the management of water resources and agricultural planning.

## Table 5: Final Prediction Results

|  |  |  |
| --- | --- | --- |
| **Test Data Sample** | **Actual Rainfall** | **Predicted Rainfall** |
| Sample 1 | Heavy Rain | Heavy Rain |
| Sample 2 | No Rain | No Rain |
| Sample 3 | Light Rain | Light Rain |
| Sample 4 | Moderate Rain | Moderate Rain |

## User Interaction

## The system architecture also incorporates features for user engagement. Service providers may log in, explore datasets, see trained and tested findings, and obtain projected datasets. Remote users may sign up, log in, and check their profiles and prediction results.

## The use of several data sources and powerful machine learning algorithms, paired with geostatistical approaches such as Kriging, considerably improves the accuracy and dependability of rainfall forecasts. The Logistic Regression model, modified by Kriging, has the best accuracy, highlighting the approach's promise for successful water resource management, especially in agriculturally reliant areas.

## Performance Metrics

* Accuracy: Measured through metrics such as Mean Squared Error (MSE) and Probability of Detection (POD).
* Comparison: The ensemble techniques, particularly Random Forest (RF) and Gradient Boosting (GB), showed superior performance in terms of prediction accuracy.

## Evaluation Tests

The accuracy of the rainfall prediction method was evaluated using the following tests:

* Mean Squared Error (MSE): Measures the average squared difference between predicted and actual values.
* Probability of Detection (POD): Measures the proportion of actual events correctly predicted.

The novelty of this study consists in the incorporation of many data sources (meteorological observations, satellite imaging, and atmospheric data) via the use of sophisticated machine learning methods. This integration enhances the precision and dependability of rainfall forecasts in comparison to conventional approaches. The work emphasises the capacity of machine learning to capture intricate spatiotemporal patterns in precipitation, hence enhancing decision-making processes in industries affected by rainfall.

# CONCLUSION

# This work shows the efficacy of combining various data sources and sophisticated machine learning algorithms with geostatistical approaches such as Kriging to improve the precision and dependability of rainfall forecasts. The Logistic Regression model, enhanced with Kriging, proved to be the most effective model, with an accuracy rate of 73.20%. By including spatial autocorrelation using Kriging, the accuracy of the forecasts was much enhanced, allowing for a more accurate representation of the intricate spatiotemporal patterns of precipitation compared to conventional techniques. These results highlight the possibility of combining several methods for improved water resource management and agricultural planning, especially in areas that rely significantly on precise rainfall predictions.

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