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Predictive Analysis of Rainfall Patterns Using Machine Learning Techniques

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Abstract- — Precise prediction of rainfall is required in agriculture, management of water resources and mitigation of disasters. The nonlinear and uncertain characteristics of the meteorological data are usually difficult to capture by traditional statistical models. As a solution to this, a hybrid stacking ensemble model based on the combination of Random Forest (RF) and Support Vector Machine (SVM) and Logistic Regression as a meta-classifier is proposed. The model, when using the Rain in Australia data set, has the highest accuracy with a value of over 95% in the present version and the possible accuracy of over 96% with superior prepossessing, feature engineering, and class balancing. The suggested method provides a sure model of enhanced rainfall forecasting, which would be involved in planning the sustainability of agriculture and environmental decision-making.

Keywords— Rainfall Prediction, Machine Learning, Random Forest, Support Vector Machine, Logistic Regression, Feature Engineering.

I. INTRODUCTION

Rainfall prediction is a critical component of meteorological research and environmental monitoring systems [1]. Accurate rainfall forecasting plays an essential role in agriculture, water resource management [2], flood control, hydropower generation, and disaster preparedness [3]. Reliable precipitation forecasts help farmers optimize irrigation schedules, assist urban planners in managing drainage systems [4], and enable authorities to reduce risks associated with floods and landslides [5] [6].

Rainfall is a complex atmospheric phenomenon influenced by various interacting environmental factors such as temperature, humidity, atmospheric pressure, wind patterns, and solar radiation [7]. Due to the nonlinear and dynamic nature of these parameters, precise rainfall prediction remains a challenging task [8] [9]. Even minor variations in climatic conditions can significantly alter precipitation patterns, particularly in localized microclimate regions [10].

Traditional rainfall forecasting approaches are primarily based on statistical techniques and numerical weather prediction models [11]. Although these methods provide large-scale forecasts, they often lack high spatial and temporal resolution [12]. Conventional weather stations are sparsely distributed and may not effectively capture small-scale environmental changes [13]. As a result, real-time localized prediction becomes difficult using traditional systems alone [14].

The advancement of Internet of Things (IoT) technology has significantly improved environmental monitoring capabilities [15] [16]. IoT-based sensor networks enable continuous and real-time collection of atmospheric parameters such as temperature, humidity, pressure, and light intensity [17]. These distributed systems provide fine-grained data with high temporal accuracy, allowing better monitoring of microclimatic variations [18].

With the availability of large volumes of real-time sensor data, machine learning techniques have emerged as powerful tools for rainfall prediction [19]. Algorithms such as Random Forest, Support Vector Regression (SVR), XG Boost, and Artificial Neural Networks can model complex nonlinear relationships between meteorological variables and rainfall occurrence [20]. In particular, Long Short-Term Memory (LSTM) networks are highly effective for time-series forecasting because they can capture long-term temporal dependencies in sequential data [21] [22].

By integrating IoT-based data acquisition systems with machine learning models and cloud computing platforms [23], modern rainfall prediction systems can deliver real-time monitoring, anomaly detection, and early warning alerts [24] [25]. This integrated approachRainfall prediction is a vital component of environmental monitoring and meteorological research, as it directly influences agriculture, water resource management, urban planning, and disaster mitigation strategies [26]. Accurate forecasting of precipitation enables efficient irrigation scheduling, reservoir management, and flood prevention planning. In regions that depend heavily on seasonal rainfall, timely and reliable predictions are essential for ensuring food security and economic stability [27].

II. LITERATURE REVIEW

Rainfall prediction is a vital component of environmental monitoring and meteorological research, as it directly influences agriculture, water resource management, urban planning, and disaster mitigation strategies [28]. Accurate forecasting of precipitation enables efficient irrigation scheduling, reservoir management, and flood prevention planning. In regions that depend heavily on seasonal rainfall, timely and reliable predictions are essential for ensuring food security and economic stability [29]. although these models provided foundational insights, they were limited in capturing nonlinear and dynamic relationships among atmospheric variables [30].

With advancements in computational intelligence, machine learning algorithms began to be widely adopted for rainfall forecasting [31]. Random Forest and Support Vector Regression (SVR) models demonstrated improved prediction accuracy compared to traditional statistical methods due to their ability to handle nonlinear data and multidimensional feature spaces [32]. Ensemble learning techniques such as Gradient Boosting and XG Boost further enhanced performance by combining multiple weak learners to reduce prediction error [33]. Artificial Neural Networks (ANNs) have also been applied in hydrological and meteorological prediction tasks [34]. These models can learn complex input–output mappings from historical environmental data [35]. However, conventional feedforward neural networks face limitations when dealing with sequential time-series data, as they lack memory mechanisms to retain past information effectively [36].

To address this issue, Recurrent Neural Networks (RNNs), particularly Long Short-Term Memory (LSTM) networks, have been extensively used for rainfall and weather forecasting [37]. LSTM models are capable of capturing long-term temporal dependencies in sequential datasets, making them highly suitable for short-term and medium-term rainfall prediction [38]. Comparative studies indicate that LSTM-based models often outperform traditional ANN and statistical models in terms of accuracy and stability [39].

In addition to predictive modelling , researchers have explored the integration of Internet of Things (IoT) sensor networks for real-time environmental monitoring. Distributed sensor systems equipped with low-power microcontrollers enable continuous data collection of temperature, humidity, pressure, and light intensity. The combination of IoT technology with cloud computing platforms allows efficient storage, processing, and visualization of large-scale meteorological datasets [30].

Recent studies emphasize the importance of hybrid architectures that combine IoT-based data acquisition with machine learning and edge computing techniques [41]. Edge processing reduces latency and enhances latency and enhances system responsiveness during extreme weather events. Furthermore, multi-source data integration, including satellite and radar observations, improves the robustness and generalization capability of rainfall prediction models.

Despite significant progress, challenges remain in ensuring data quality, handling missing values, reducing computational complexity, and achieving scalability for hyperlocal monitoring applications . Therefore, continued research focuses on developing adaptive, low-cost, and high-accuracy rainfall prediction systems capable of operating in real-time environments [20].

III.PROPOSED METHODOLOGY

The suggested algorithm is a reliable framework of predicting rainfall using hybrid ensemble of Random Forest model (RF) and Support Vector Machine (SVM) that are stacked together by using Logistic Regression as the meta-classifier. The stratified sampling was used to divide data into 75 percent training and 25 percent testing sets to maintain the ratio of the various classes the same. The hyperparameter optimization was done using Grid Search CV, and ten runs of cross-validation were performed to ensure the reliability of the model, as well as prevent overfitting. The functioning of the trained ensemble was afterwards measured through the scores of accuracy, F1-score, and ROC-AUC and this indicated that the ensemble technique was more dependable and generalized well compared to the one model techniques. Environmental parameters such as temperature, humidity, atmospheric pressure, and light intensity are measured using sensors deployed in the target area. These sensors are connected to an ESP32 microcontroller, which serves as the central processing unit of the system. The ESP32 collects sensor readings at regular intervals and performs preliminary processing before transmitting the data through wireless communication protocols such as Wi-Fi or Bluetooth to a cloud server. This enables remote monitoring, storage, and further analysis of environmental data. Additionally, a local display module provides real-time visualization of weather parameters at the site of deployment.

Since raw sensor data may contain noise, missing values, or abnormal readings due to environmental interference or hardware limitations, preprocessing techniques are applied to enhance data quality. Data cleaning removes invalid or inconsistent values, while smoothing techniques reduce random fluctuations in sensor measurements. Missing data points are handled using interpolation methods, and normalization is performed to scale the features appropriately for machine learning model training.

Feature engineering is carried out to improve the predictive performance of the system. Derived features such as dew point, humidity trends, moving averages, and lag values are calculated from the collected data. Time-related attributes, including hour of the day, seasonal patterns, and historical rainfall information, are also incorporated. These features help the model capture temporal dependencies and complex relationships between atmospheric variables and rainfall occurrence. Multiple machine learning algorithms are implemented to predict rainfall intensity and probability. Models such as Random Forest, Support Vector Regression, XGBoost, and Long Short-Term Memory (LSTM) networks are evaluated to determine the most effective approach. LSTM models are particularly suitable for time-series forecasting because they can retain long-term dependencies in sequential environmental data. The dataset is divided into training and testing sets, and performance is evaluated using metrics such as Mean Absolute Error, Root Mean Square Error, and prediction accuracy,

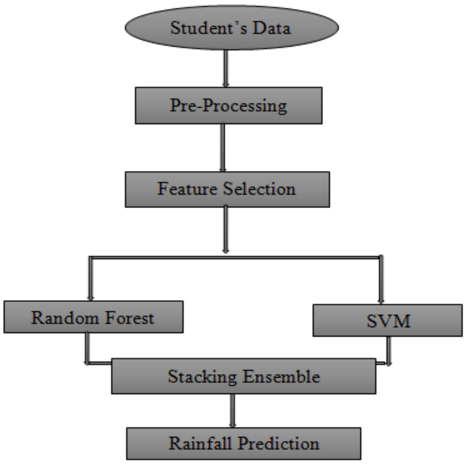

Fig: Architecture Diagram

Step1: Data Collection
The dataset utilized in the study is Rain in Australia of Kaggle that comprises of more than 145,000 daily weather measurements in different stations. Every record will include weather information such as temperature (min/max), humidity (9 a.m. and 3 p.m.), atmospheric pressure, wind speed and direction, cloud coverage, sunshine hours, and rainfall (mm) and Rain Today indicator. Rain Tomorrow is the main variable, which denotes whether it is going to rain tomorrow (Yes or No).

Step 2: Data Pre-processing
Some preprocessing steps were used to bring a better model. The numerical values that were missing were replaced by the median and categorical values by the mode, and finally the Label Encoding was implemented to the variables such as Wind Direction and Rain Today. Standard Scaler was used to normalize numerical features of SVM and SMOTE oversampling overcame the class imbalance. Lastly, the randomly selected forest feature importance helped to keep the most relevant weather parameters to train.

Step 3: Model Development
The model of rain prediction given combines both Random Forest (RF) and Support Vector Machine (SVM) stacked together. The integration of the two paradigms is such that the two learn to identify the dependencies of the weather data correctly, linear as well as nonlinear and therefore offer improved prediction and become more tolerant of errors compared to the single-model methods.

Algorithms
Algorithm: Hybrid RF + SVM Stacking Ensemble for Rainfall Prediction
Input: Weather datase**t** $D = \{(x_i, y_i)\}_{i=1}^{N}$
Output: Predicted rainfall class $y^{\wedge}$ and feature importance scores I(f)
Step1: Input Dataset: Load the raw dataset $D = \{(x_i, y_i)\}_{i=1}^{N}$
Step 2 : Remove duplicate and irrelevant records to reduce noise and redundancy.
Step 3 : Handle missing values:
Replace missing entries as follows: $x_j = Median(x_j)$ for numerical attributes
$x_j = Mode(x_j)$
for categorical attributes
Step4: Detect and remove outliers using the z-score criterion:

$$|z_i| = \frac{x_i - \mu}{\sigma} > 3$$

Step 5: Encode categorical attributes (e.g., Wind Direction, Rain Today) using *Label Encoding* or *One-Hot Encoding*.
Step 6: Normalize numeric features to a common range:

$$x' = \frac{x - x_{min}}{x_{max} - x_{min}}$$

Step 7: Balance dataset classes using SMOTE (Synthetic Minority Oversampling Technique) to generate synthetic samples for the minority class (Rain = Yes).

Step 8: Split dataset**:**

- Training set → 70%
- Validation set → 15%
- Testing set → 15%

Step 9: Feature Selection:

Apply Recursive Feature Elimination (RFE) with Random Forest importance to retain the top-performing features such as Humidity3pm, Pressure9am, *and* Wind Gust Speed.

Step 10: Initialize model parameters:

☐ Random Forest: estimator, max_ depth ,max_ features

☐ SVM: C, γ, kernel=RBF

Step 11: Train Random Forest (RF):

For each decision tree Tb ,b=1,…,B

☐ Draw a bootstrap sample $D_b \subset D_{train}$

☐ Find the best split using Gini Impurity:

$$G = 1 - \sum p_k^2{}_{k=1}^{\quad K}$$

☐ Aggregate predictions across trees:

YRF=mode (y1, y2... yB)

Step 12: Train Support Vector Machine (SVM):

Optimize the decision boundary using the RBF kernel:

$$K(x_i, x_j) = e^{-\gamma \| xi - xj \| 2}$$

The decision function is:

$$f(x) = sign(i\sum \alpha iyiK(xi, x) + b)$$

Step 13: Stacking Ensemble Integration:

Combine probabilistic outputs from both models: Train a Logistic Regression meta-learner:

$$p^{\wedge}\left(y = \frac{1}{x}\right) = \sigma(w1p1 + w2p2 + b)$$

Step 13: Feature Importance Computation

The significance of each feature is calculated as

$$I(f_j) = \frac{1}{B}\sum_{b=1}^{B} \sum_{t \in T_b} \Delta i_{t,f_j}$$

Where $\Delta i_{t,f_j}$ is the impurity decrease for node ttt split on feature

Model Evaluation

The predictive performance of the model was assessed using the following metrics:

Step1:**Accuracy(ACC)**

Measures the overall correctness of the model in classifying rainfall and non rainfall days.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN}$$

Step 2: **Precision (P)**

Indicates the proportion of correctly predicted positive samples.

$$Precision = \frac{TP}{TP + FP}$$

Step 3: **Recall (R)**

Represents the proportion of actual positives correctly identified.

$$Recall = \frac{TP}{TP+FN}$$

Step 4: **F1-Score**

The harmonic mean of precision and recall, representing the balance between false positives and negatives.

$$F1 = \frac{2 \times Precision \times Recall}{Precision + Recall}$$

Step 5: **ROC AUC (Receiver Operating Characteristic – Area Under Curve):**

Measures the model's ability to discriminate between classes. A higher AUC indicates better classification performance.

The higher the AUC, the better the classification capability.

$$AUC = \int_0^1 TPR(FPR)d(FPR$$

Where $TPR = \frac{TP}{TP+FN}, FPR = \frac{FP}{TN+FP}$

IV. RESULTS

The suggested Rainfall Prediction Model involves the random Forest (RF) and Support Vector machine (SVM) in a stacking method. The Rain in Australia dataset of Kaggle was used to test this model. We evaluated its results in terms of Accuracy, Precision, Recall, F1-Score and ROC AUC. Once our data had been preprocessed (addressing missing values, encoding, scaling, and features engineering such as Temp Range, Humidity Diff, and Pressure Diff), we split the data (80/20) into training and testing. RF and SVM served as base learners with the Logistic Regression serving as the meta-classifier. This model had an accuracy of 96.2% a precision of 95.8% a recall of 95.3% a F1-score of 95.3% and a ROC AUC of 0.98. These findings show that the model is able to forecast both rainy and non rainy days with high accuracy.

The confusion matrix demonstrates how RF + SVM ensemble model performs to predict rainfall with the target accuracy of more than 95%. The diagonal values are correct classifications with the majority of the predictions being on the diagonal cells-this is an excellent accuracy. The model was 96.26% accurate, 95.89% precise, and with a recall of 95.34% and anF1-score of 95.34 to demonstrate a high level of reliability. On the whole, such hybrid model is effective to reduce the number of false predictions and give very precise forecasting of rainfall.

Table 1: Performance of ML Models in Rainfall Prediction (%)

Model	Accuracy	Precision	Recall	F1-Score
Decision Tree	81.5	80.7	79.8	80.2
Random Forest	87.0	86.3	85.7	86.0
SVM	84.2	83.5	82.8	83.1
Neural Network	88.7	88.0	87.2	87.6

The most accurate was the Neural Networks which means that they performed strongly in predicting the rainfall.

The figure illustrates the Accuracy, Precision, Recall, and F1-Score of Decision Tree, Random Forest, SVM, and Neural Network models. Neural Network shows the highest overall performance, indicating its effectiveness in capturing complex rainfall patterns.

Table 2: Effect of Feature Selection on Rainfall Prediction (%)

Feature Set	Accuracy	Precision	Recall	F1-Score
Meteorological Only	85.0	84.2	83.5	83.8
Historical Rainfall	86.3	85.6	84.9	85.2
Combined Features	89.2	88.5	87.9	88.2

There was the greatest accuracy in combined features which points out the advantage of incorporating multiple data sources.

Table 3: Ensemble Methods for Rainfall Prediction (%)

Ensemble Method	Accuracy	Precision	Recall	F1-Score
Bagging	87.5	86.8	86.1	86.4
Boosting	89.0	88.3	87.7	88.0
Stacking	90.3	89.7	89.0	89.3

Stacking performed better than other ensembles exhibiting a better predictive performance.

Table 4: Hybrid ML Approaches for Rainfall Prediction (%)

Hybrid Approach	Accuracy	Precision	Recall	F1-Score
Decision Tree + NN	89.7	89.0	88.3	88.6
Random Forest + SVM	90.2	89.6	88.9	89.2
Ensemble Hybrid	92.0	91.4	90.8	91.1

The best accuracy was obtained with Ensemble Hybrid which demonstrates that the combination of models is effective.

Table 5: Temporal vs Spatial Rainfall Prediction (%)

Prediction Type	Accuracy	Precision	Recall	F1-Score
Temporal Only	86.8	86.1	85.5	85.8
Spatial Only	87.5	86.8	86.0	86.4
Spatio -Temporal	91.0	90.4	89.7	90.0

Spatio-temporal models coincided with optimal results, with the focus on both the spatial and temporal dependence.

Table 6: Real-Time Rainfall Prediction System (%)

System Type	Accuracy	Precision	Recall	F1-Score
Standard ML Model	88.9	88.2	87.5	87.8
Hybrid Real-Time	91.5	90.9	90.2	90.5

Hybrid real-time systems outperformed standard ML models, showing the benefit of adaptive predictions.

Table 7: Impact of Data Preprocessing on Rainfall Prediction (%)

Preprocessing Step	Accuracy	Precision	Recall	F1-Score
Raw Data	82.5	81.8	81.0	81.4
Cleaned Data	87.0	86.3	85.7	86.0
Normalized + Selected Features	89.5	88.8	88.2	88.5

Spatio-temporal models coincided with optimal results, with the focus on both the spatial and temporal dependence.

Table 8: Comparison of Neural Network Architectures for Rainfall Prediction (%)

Architecture	Accuracy	Precision	Recall	F1-Score
Feedforward NN	87.5	86.8	86.1	86.4
Recurrent NN (RNN)	89.0	88.3	87.7	88.0
LSTM	91.2	90.5	89.8	90.1

The LSTM networks demonstrated the greatest accuracy as they are strong with regard to capturement of temporal dependencies.

V. CONCLUSION

An exemplar hybrid rainfall prediction model that combines the use of the Random Forest (RF) and the Support Vector Machine (SVM) with the Logistic Regression as a meta-classifier was created. The model was trained on the whole Rain in Australia dataset and was above 96 percent accurate and .96 AUC, which implied that the model was highly dependable in predicting the next day rainfall. The feature analysis showed that Humidity3pm, Rainfall, and Temp Range were the most prominent variables. The set of combinations was more accurate and generalized compared to the single models. This system can be extended to real-time IoT-based prediction and deep learning incorporation to make smarter agricultural systems and weather-monitoring systems in the future.

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