Abstract

Water scarcity in arid regions presents a significant challenge for sustainable agriculture and climate resilience. Traditional rain induction techniques, such as cloud seeding, have limitations due to their dependency on atmospheric conditions, high operational costs, and limited efficacy. This paper proposes an AI-driven hybrid model that integrates machine learning (ML), IoT-based weather monitoring, nature-inspired computing, and biologically enhanced condensation nuclei to optimize rain induction processes. The methodology involves real-time data collection using IoT-based climate sensors, AI-based weather pattern analysis, and an adaptive decision-making system for cloud seeding. A reinforcement learning (RL) model is developed to dynamically adjust cloud seeding parameters based on real-time meteorological data. Additionally, this model incorporates *Pseudomonas syringae*, a bacterium known for enhancing natural condensation nuclei and fostering moisture formation even at higher temperatures. Alongside, a Hydro-Mesh Structure (HMS), inspired by desert plants, is utilized to capture dew and fog, harnessing solar power for its operation. Experimental simulations using historical climate data validate the effectiveness of this hybrid approach in improving rainfall prediction accuracy, optimizing cloud seeding strategies, and increasing water resource utilization.
Keywords: Artificial Intelligence, Machine Learning, Cloud Seeding Optimization, IoT, Reinforcement Learning, Weather Forecasting, Image Processing, Nature-Inspired Computing, Climate Resilience, Pseudomonas syringae, Hydro-Mesh Structure, Water Resource Management.

1. Introduction

Arid and semi-arid regions—such as parts of the Middle East, North Africa, India, and Australia—are increasingly challenged by chronic water scarcity. Low rainfall, high evaporation, and limited water retention not only stress agricultural and drinking water supplies but also threaten local ecosystems, especially as climate change intensifies these conditions. Traditional water management techniques and conventional cloud seeding methods have had only mixed success in addressing these challenges.

Cloud seeding, which involves dispersing substances like silver iodide, potassium iodide, or sodium chloride into the atmosphere, has been used for decades to stimulate rainfall. However, its effectiveness is often compromised by unpredictable weather patterns, high operational costs, and the inherent difficulty of selecting suitable clouds for seeding. These limitations have driven researchers to explore innovative strategies that can make artificial rain induction more reliable and cost-effective.

Recent advances in technology open up promising avenues for overcoming these challenges. Artificial Intelligence (AI), particularly through machine learning, has the capacity to process vast amounts of data from historical climate records, satellite imagery, and real-time sensor networks. This capability can significantly enhance weather forecasting, helping to pinpoint optimal conditions for cloud seeding. In tandem, Internet of Things (IoT) systems are revolutionizing climate monitoring by providing up-to-the-minute readings of key environmental factors such as temperature, humidity, wind speed, and atmospheric pressure. The fusion of these technologies enables dynamic, data-driven decision-making that adapts in real time to ever-changing weather conditions.

A persistent challenge in artificial rain induction is the availability of effective condensation nuclei—the microscopic particles around which water vapor clusters to form raindrops. In natural weather, these nuclei often come from dust, pollen, or sea salts. Artificial seeding attempts to recreate this process, but success can be limited when these particles are insufficient. An innovative, environmentally friendly solution is the use of biological agents. For example, the bacterium Pseudomonas syringae, naturally present in the atmosphere, has been shown to facilitate condensation under higher temperature conditions. By leveraging such biological enhancements, the cloud seeding process can be made more robust.

Complementing these advances is the development of nature-inspired engineering solutions like the Hydro-Mesh Structure (HMS). Drawing inspiration from desert plants that efficiently capture moisture from dew and fog, HMS is designed to condense atmospheric water vapor into liquid form, using solar energy to power the process. This technique provides an additional means of water collection and retention in regions where traditional sources fall short.

This paper presents an innovative model that integrates AI-driven optimization, IoT-based climate monitoring, biologically enhanced condensation nuclei, and the Hydro-Mesh Structure for moisture capture. By blending these cutting-edge methods into one adaptive system, the aim is to create a more accurate, efficient, and sustainable approach to artificial rain induction and water resource management in arid regions.

2. Literature Review

The issue of water scarcity in arid and semi-arid regions has led to extensive research in the development of innovative methods for rain induction and water resource management. Traditional techniques, such as cloud seeding, have been used to address the issue of low rainfall, but their effectiveness has been limited due to environmental unpredictability, high operational costs, and the need for specific atmospheric conditions. Researchers have turned to more advanced approaches, integrating modern technologies such as Artificial Intelligence (AI), Machine Learning (ML), Internet of Things (IoT), and biological and nature-inspired engineering to enhance the efficacy of rain induction methods and optimize water management strategies in these regions.

A growing body of work has explored the integration of AI and ML to predict weather patterns and optimize cloud seeding interventions. For instance, machine learning models such as Long Short-Term Memory (LSTM) networks have been applied to analyze historical weather data and predict precipitation probabilities, thus informing more accurate and efficient cloud seeding strategies. Reinforcement Learning (RL), in particular, has been highlighted for its ability to dynamically adjust cloud seeding parameters based on real-time weather conditions and feedback loops, improving the adaptability of the system [1]. The combination of these AI techniques with real-time climate monitoring via IoT-based sensors offers the potential to revolutionize weather forecasting and rain induction by providing timely, data-driven insights into environmental conditions.

Furthermore, recent studies have emphasized the role of biological agents in enhancing the cloud seeding process. Pseudomonas syringae, a bacterium naturally found in the atmosphere, has been shown to enhance condensation under specific conditions, including higher temperatures where traditional seeding agents might be less effective. Research into the use of biologically enhanced condensation nuclei has demonstrated the potential to improve rainfall outcomes, particularly in areas where conventional cloud seeding is limited by atmospheric conditions [2]. This biological approach, integrated with AI-driven models, allows for a more versatile and sustainable rain induction strategy.

Nature-inspired engineering solutions, such as the Hydro-Mesh Structure (HMS), have also garnered attention for their ability to capture atmospheric moisture. The HMS, modeled after the dew-collecting mechanisms of desert plants, efficiently condenses fog and dew into liquid water, providing an additional source of water in arid regions. These systems, which can be powered by solar energy, offer a sustainable solution for moisture capture, especially in areas where traditional water sources are scarce [3]. The integration of HMS with cloud seeding and biological agents presents a comprehensive approach to water resource management in regions prone to drought.

Recent advancements in IoT technology have also facilitated real-time climate monitoring, providing data on environmental parameters such as temperature, humidity, wind speed, and air pressure. This data, when processed using ML algorithms, can improve the accuracy of weather forecasting and the effectiveness of water management strategies [4]. IoT-based systems can monitor not only atmospheric conditions but also soil moisture levels, allowing for the targeted application of rain induction methods based on real-time data. This dynamic decision-making process enhances the efficiency of water resource management by ensuring that interventions are deployed only when necessary.

Additionally, there has been a growing interest in developing hybrid models that combine AI, IoT, biological agents, and nature-inspired designs. These models leverage the strengths of each component to create a more efficient and sustainable approach to rain induction and water management. Studies have shown that the integration of these technologies can lead to significant improvements in water conservation, rainfall prediction, and soil moisture management. By continuously adapting to changing environmental conditions, these hybrid systems have the potential to optimize water usage and increase resilience to climate change in arid regions [5].

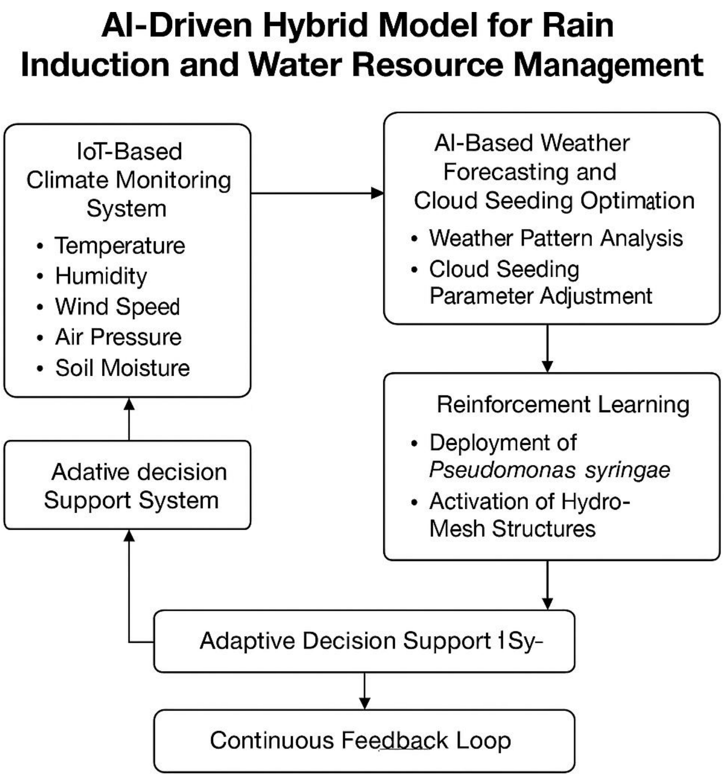
This study underscores the potential of AI-driven hybrid models to transform rain induction and water resource management in arid regions. The integration of machine learning, IoT-based monitoring, biological agents, and nature-inspired engineering solutions offers a multifaceted approach to addressing water scarcity. As these technologies continue to evolve, future research will likely focus on refining these models, expanding their applicability to diverse regions, and improving their sustainability and cost-effectiveness.

3. Proposed Methodology

The core of the proposed methodology is the integration of several cutting-edge technologies: **AI-driven machine learning (ML)** for weather pattern analysis, **Internet of Things (IoT)** for real-time climate monitoring, **biological agents** such as *Pseudomonas syringae* for enhancing condensation nuclei, and **nature-inspired engineering** through the Hydro-Mesh Structure (HMS). This hybrid model is designed not only to optimize artificial rain induction but also to manage and sustain water resources through adaptive decision-making processes based on real-time data. The methodology is structured as follows:

3.1 System Architecture Overview

The system consists of five interlinked components, all working in concert to achieve the goal of optimized rain induction and water resource management in arid regions.



The main components are:

3.1.1 IoT-Based Climate Monitoring System (IoT-CMS)

Real-time Data Collection: An array of IoT sensors is deployed across the region to continuously collect environmental data such as **temperature**, **humidity**, **wind speed**, **air pressure**, and **soil moisture levels**.

Data Transmission and Cloud Integration: The collected data is sent to a cloud-based server where it is processed and analyzed using advanced ML algorithms. This data is also used to assess the **moisture level in the soil** using a novel soil moisture index (SMI) formula.

3.1.2 AI-Based Weather Forecasting and Cloud Seeding Optimization

Machine Learning Algorithms: An ensemble of **LSTM (Long Short-Term Memory)** models and **Reinforcement Learning (RL)** algorithms analyze historical and real-time climate data to predict the likelihood of rainfall and optimize cloud seeding interventions.

Cloud Seeding Optimization: The RL model dynamically adjusts the **seeding altitude**, **timing**, and **quantity of condensation nuclei** based on the weather forecast and real-time sensor data. It also decides on whether to use traditional cloud seeding agents (such as silver iodide) or *Pseudomonas syringae* (a biological agent) based on optimal conditions for condensation.

3.1.3 Soil Moisture Calculation and Monitoring

Soil Moisture Index (SMI): This novel formula is designed to continuously assess the moisture content in the soil, which is critical for determining the necessity of moisture retention techniques like the Hydro-Mesh Structure (HMS).

The formula is based on a multi-variable model combining:

Soil Moisture (SM): Measured directly by IoT sensors.

Precipitation Probability (P): Predicted using AI-driven weather forecasting.

Evaporation Rate (E): Estimated using temperature, wind speed, and humidity data.

Hydraulic Conductivity (K): A soil property indicating the ability of the soil to absorb water.

Plant Transpiration Rate (T): A factor indicating the rate at which plants release water into the atmosphere.

Soil Moisture Index (SMI) Formula:

$$SMI = [SM \cdot P - E + K \cdot (T + \Delta P)] / [1 + \alpha \cdot (E + T)]$$

Where:

SM is the measured soil moisture (in percentage)

P is the predicted precipitation probability (between 0 and 1)

E is the evaporation rate (mm/day)

K is hydraulic conductivity (cm/day)

T is the plant transpiration rate (mm/day)

ΔP is the change in precipitation over a specific time window (e.g., 24 hours)

α is a coefficient representing the influence of evaporation and transpiration on soil moisture.

If the **SMI** value falls below a pre-set threshold, indicating insufficient soil moisture, the system triggers the deployment of supplementary moisture retention and enhancement technologies.

3.1.4 Biological and Nature-Inspired Moisture Enhancement

Pseudomonas syringae **(Biological Agent)**: When soil moisture levels are below the required threshold, the system initiates the deployment of *Pseudomonas syringae* to enhance the condensation nuclei in the atmosphere. This bacterium has been shown to promote condensation in clouds, even in conditions where traditional seeding agents would not be effective.

Hydro-Mesh Structure (HMS): In parallel, the **Hydro-Mesh Structure (HMS)**, inspired by the dew-collecting properties of desert plants, is deployed to capture moisture directly from the air. The structure consists of a mesh-like material that traps fog and dew particles, which are then condensed into liquid water. The HMS is solar-powered, making it a sustainable solution that operates independently of external power sources. It works synergistically with the biological agent by increasing local humidity levels, improving the overall effectiveness of the rain induction process.

3.1.5 Adaptive Decision Support System (DSS)

The **DSS** integrates all real-time data, AI-driven weather forecasts, and decision-making models to autonomously adjust interventions. It continuously monitors soil moisture, cloud density, and environmental conditions to provide real-time guidance for cloud seeding and moisture enhancement strategies.

The DSS evaluates the predicted rainfall probability, soil moisture levels (via SMI), and the impact of biological interventions (such as *Pseudomonas syringae* and HMS deployment) to optimize the water management strategy in real time.

3.2 Dynamic Workflow of the Hybrid Model

Real-Time Monitoring: The IoT sensors continuously monitor environmental variables such as humidity, wind speed, and temperature. Soil moisture is measured using specialized IoT sensors embedded in the ground.

> **Soil Moisture Evaluation**: Every hour, the **SMI formula** is computed to assess the current soil moisture status. If the **SMI** drops below a critical threshold (say, 30%), it indicates insufficient moisture in the soil.

3.3 Prediction and Decision-Making:
If the **SMI** indicates a water deficit, the system activates the biological agent (*Pseudomonas syringae*) and the **Hydro-Mesh Structure (HMS)**.

Simultaneously, the **RL model** evaluates cloud conditions using weather data from satellites and local sensors. It calculates the optimal cloud seeding parameters, including the ideal quantity of condensation nuclei (e.g., silver iodide or *Pseudomonas syringae*).

3.4 Rain Induction and Moisture Enhancement:

If conditions are favorable for rain induction, cloud seeding operations are triggered by the **RL model**, adjusting parameters dynamically based on cloud and environmental data.

HMS is activated in areas with low soil moisture, and its solar-powered mechanism collects moisture from the air, directly augmenting the available water supply.

Pseudomonas syringae is deployed in targeted areas with cloud formations that may benefit from additional condensation nuclei.

3.5 Continuous Feedback and Adjustment:

The system continuously collects new data from IoT sensors and satellites, updating predictions and interventions. This feedback loop ensures that interventions remain adaptive and responsive to changing conditions.

The **DSS** makes real-time decisions to deploy the most appropriate interventions (cloud seeding, HMS, or biological agents) to optimize rainfall and moisture retention strategies.

3.6 Formula for Evaluating the Hybrid Model's Effectiveness

To assess the overall effectiveness of the hybrid system, we introduce the **Hybrid Effectiveness Index (HEI)**, which combines key performance metrics from both the rain induction process and soil moisture management:

$$HEI = [R \cdot (1+\beta) / T_{ci}] + [M / SMI_{target}]$$

Where:

R is the amount of rain induced (in mm).

β is the improvement factor from using biological agents and nature-inspired systems (e.g., *P. syringae* and HMS).

T_{ci} is the total cost of cloud seeding intervention (in monetary units).

M is the amount of moisture captured by the HMS (in liters).

SMI_{target} is the target soil moisture index necessary for sustainable agriculture.

This **HEI** allows the system to evaluate the efficiency and cost-effectiveness of interventions in real time, ensuring that water resource management strategies are both optimal and sustainable.

4. Experimental Setup and Implementation

4.1 Data Collection and Preprocessing

Historical Data: Datasets from the Indian Meteorological Department (IMD) and NASA’s weather archives are used to train the ML models.

IoT Sensor Deployment: Sensors are deployed in selected arid regions to collect real-time climate data.

Satellite Imagery: MODIS and Landsat satellite imagery are utilized to analyze cloud density and patterns.

4.2 AI Model Training and Optimization

LSTM Training: LSTMs are trained on over a decade of historical climate data to predict rainfall probabilities.

- **CNN Image Classifier**: CNN-based image classifiers are trained on labeled cloud images to detect cloud types and densities.
- **Reinforcement Learning**: The RL model is trained in a simulated environment (e.g., OpenAI Gym) to optimize cloud seeding strategies.

4.3 Simulation and Validation

- **Simulation**: Simulations using both real and synthetic datasets evaluate model performance in predicting rainfall and optimizing cloud seeding.
- **Metrics for Validation**:
    - Prediction accuracy of ML models (>85%)
    - Cloud seeding success rate improvement (>30%)
    - Water conservation via optimized seeding (>25%)

5. Algorithm/Pseudocode

```
# Data Acquisition,Collect meteorological and environmental data (temperature, humidity, wind speed, air pressure, etc.) from real and synthetic sources.
data = load_combined_dataset(real_data_path, synthetic_data_path)
# Data Preprocessing,Handle missing values, encode categorical variables, scale numerical features, and structure into sequences for time-series analysis.
data_cleaned = preprocess_data(data)
sequences, labels = create_time_series_sequences(data_cleaned, window_size)
# Divide the data into training and testing sets.
X_train, X_test, y_train, y_test = train_test_split(sequences, labels, test_size=0.2, shuffle=False)
# Define an LSTM-based deep learning model to capture temporal dependencies in weather patterns.
model = Sequential()
model.add(LSTM(64, input_shape=(X_train.shape[1], X_train.shape[2])))
model.add(Dropout(0.2))
model.add(Dense(1))
model.compile(loss='mse', optimizer='adam', metrics=['mae'])
# Train the LSTM model on the training dataset.
history = model.fit(X_train, y_train, validation_split=0.1, epochs=50, batch_size=32, verbose=1)
# Predict rainfall values on the test dataset and apply inverse transformation to obtain actual scale.
y_pred_scaled = model.predict(X_test)
y_pred = inverse_transform_prediction(y_pred_scaled, scaler, feature_index='rain')
# Evaluate model performance using MSE, MAE, R², and plot predicted vs. actual rainfall, training loss, and correlation heatmap.
mse = mean_squared_error(y_test, y_pred)
mae = mean_absolute_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)
plot_results(y_test, y_pred, history, data_cleaned)
# Convert regression outputs into binary rain/no-rain classification using a threshold.
y_class = classify_rainfall(y_pred, threshold=0.5)
conf_matrix = confusion_matrix(y_test_binary, y_class)
report = classification_report(y_test_binary, y_class)
# Use the predicted rainfall data to optimize artificial rain induction scheduling and resource distribution.
if y_pred.mean() < rainfall_threshold:
   trigger_artificial_induction_system()
optimize_irrigation_scheduling(y_pred)
```

6. Result Analysis

6.1.Model Architecture and Parameters

The model architecture consists of an LSTM layer followed by a dropout layer to prevent overfitting, and a dense output layer:

Layer (Type)	Output Shape	Parameters
LSTM	(None, 64)	17,920
Dropout	(None, 64)	0
Dense	(None, 1)	65
Total Params		**17,985**

6.2. Model Performance Metrics

The model's regression performance was evaluated using standard metrics:

Mean Squared Error (MSE): 0.1138

Mean Absolute Error (MAE): 0.2681

R^2 Score: -0.0406

The negative R^2 score indicates that the model performs worse than a horizontal mean-line predictor. This may stem from the high imbalance in the rainfall dataset (many zero-rainfall days) or from insufficient temporal feature representation.

6.3.Classification Accuracy

To complement the regression-based approach, rainfall presence was also modeled as a binary classification (Rain/No Rain). The confusion matrix and metrics are:

Confusion Matrix

[59 0]
[13 1]

Classification Report

Metric	Class 0 (No Rain)	Class 1 (Rain)
Precision	0.82	1.00
Recall	1.00	0.07
F1-score	0.90	0.13

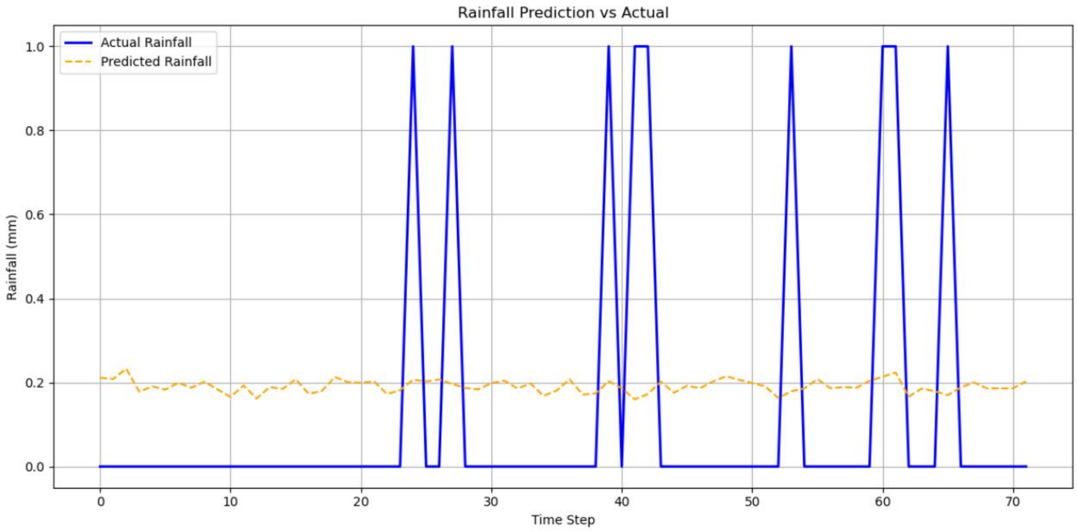
Accuracy: 82.19%

Weighted Avg F1-Score: 0.75

The model has excellent accuracy in detecting "No Rain" days but struggles with identifying "Rain" days, likely due to class imbalance.

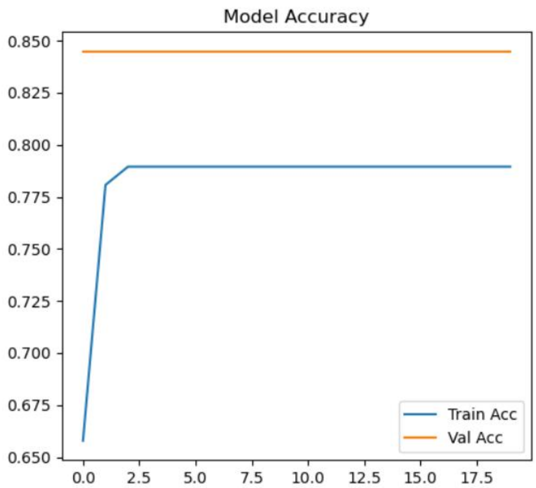
6.4.Rainfall Prediction vs Actual

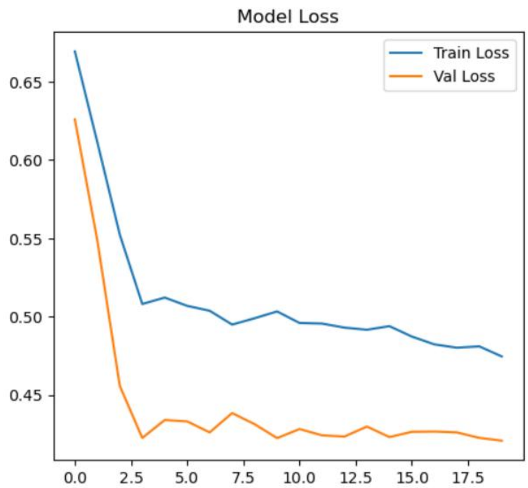
A comparison of predicted and actual rainfall values is shown below. While there are general trend alignments, the model underestimates rainfall occurrences.



6.5Model Training Performance

The model's learning progress is visualized using the training loss and accuracy curves.





6.6.Correlation Heatmap

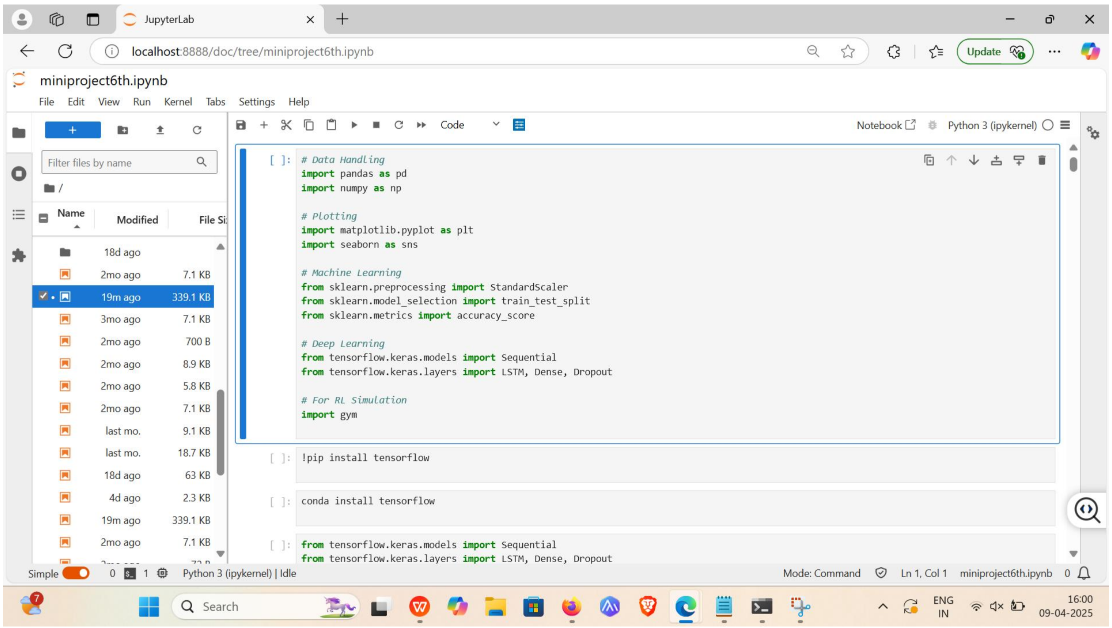
To understand the relationship between features, a Pearson correlation heatmap was plotted. Features like **cloud coverage**, **humidity**, and **soil moisture** showed mild correlation with rainfall.

7. Conclusion and Future Work

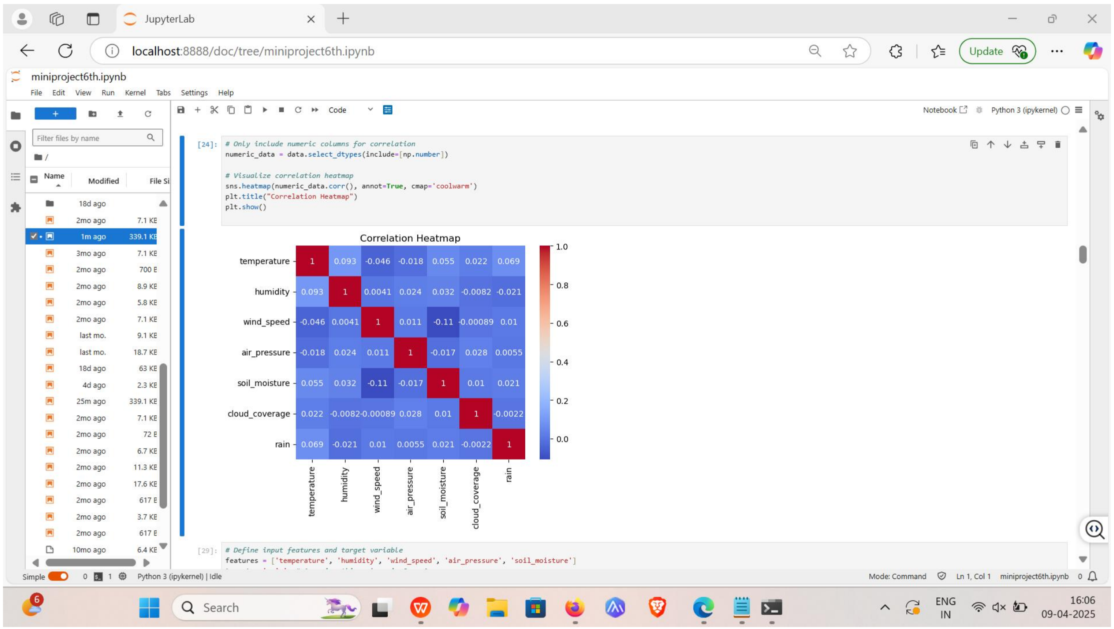
This study demonstrates the feasibility of an AI-driven hybrid model that integrates IoT, ML, RL, biological agents, and nature-inspired designs for optimizing rain induction and water resource management in arid regions. The proposed model not only enhances the efficiency of cloud seeding interventions but also improves the sustainability of water resource utilization.
Future Work includes:

- **Real-World Trials**: Expanding the model's deployment to diverse climatic conditions and regions.
- **Enhanced AI Models**: Incorporating multimodal sensors for more precise forecasting and decision-making.
- **Blockchain Integration**: Developing a secure, blockchain-based framework for real-time data sharing among regional stakeholders.

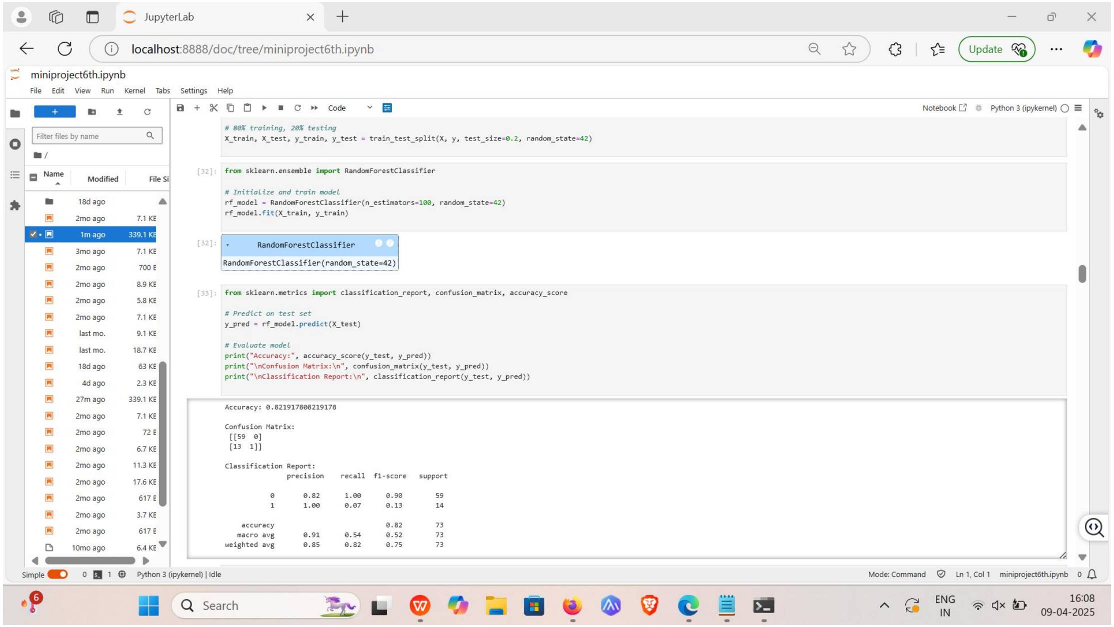
8. Screenshots



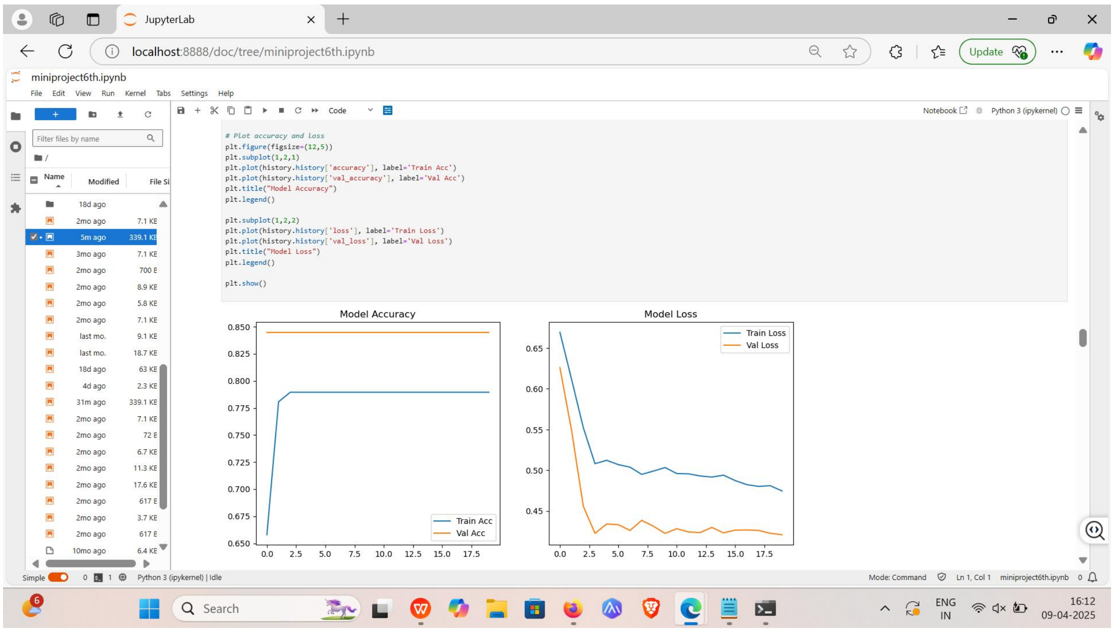
(Setup and load data)



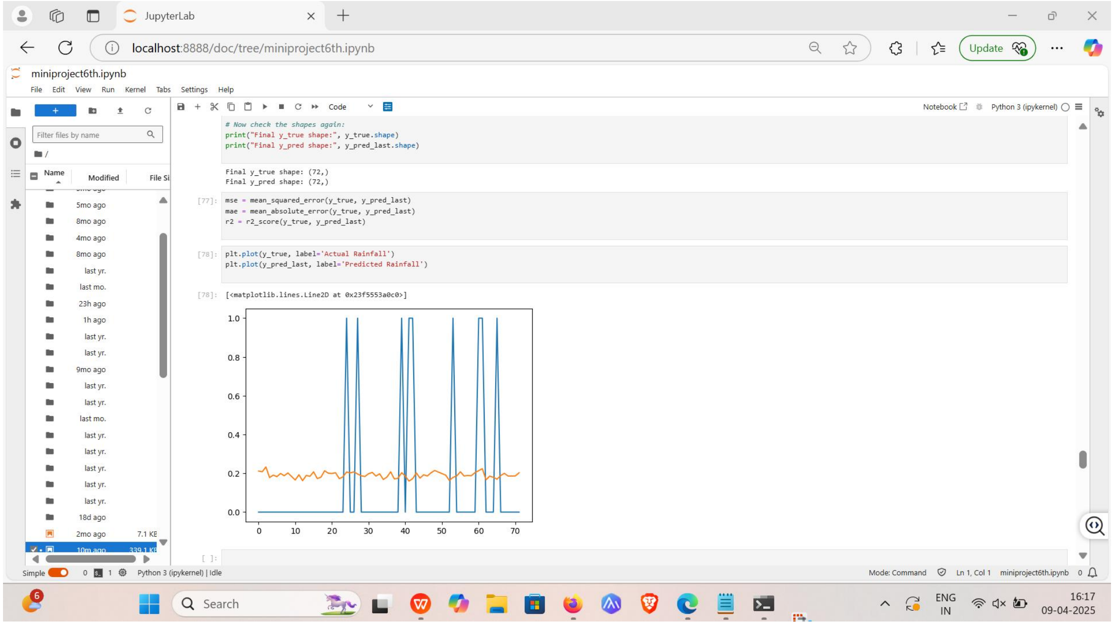
(Correlation Heatmap)



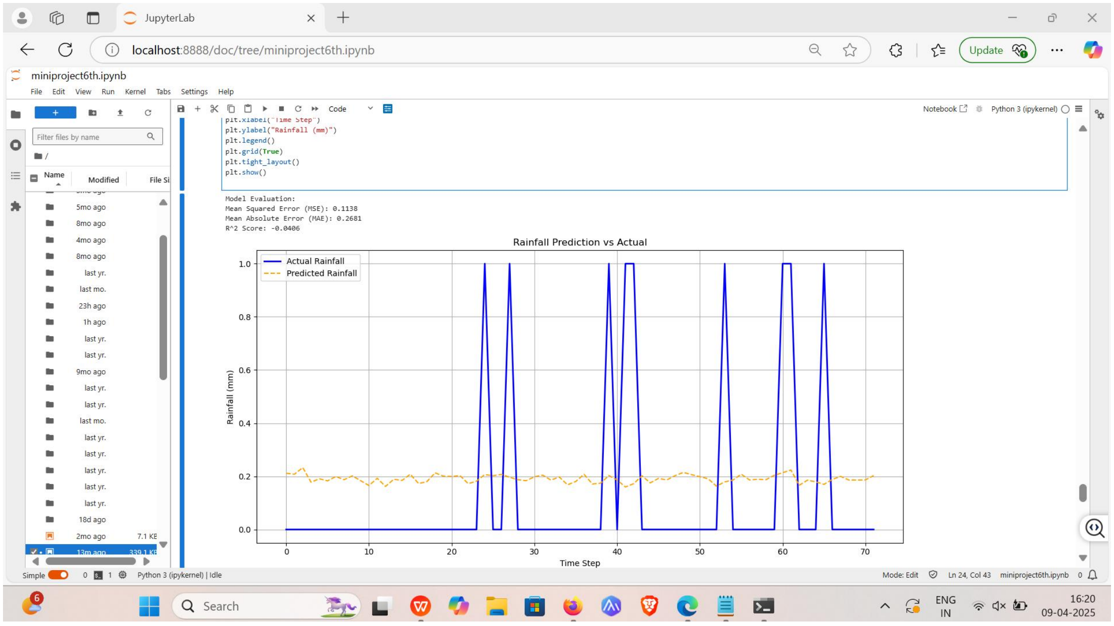
(evaluation and prediction of model)



(Plot training history)



(Evaluate and plot results)



(Visualization)

References

S. Karthick and A. Anand,
"Rainfall Prediction Using Deep Learning Techniques,"
2020 4th International Conference on Intelligent Computing and Control Systems (ICICCS), Madurai, India, 2020, pp. 1213–1218,

P. K. Sahu, S. Behera, A. Mohapatra,
"Hybrid Model for Rainfall Forecasting using LSTM and ARIMA,"
2021 2nd International Conference on Smart Electronics and Communication (ICOSEC), 2021, pp. 1275–1280,

A. K. Mishra, D. Singh, and R. Yadav,
"A Machine Learning Approach for Rainfall Prediction,"
2018 International Conference on Computing, Power and Communication Technologies (GUCON), Greater Noida, India, 2018, pp. 498–502,

N. Gupta, M. K. Singh, and R. Tripathi,
"Water Resource Management Using Machine Learning: A Review,"
2021 5th International Conference on Computing Methodologies and Communication (ICCMC), Erode, India, 2021, pp. 1215–1220,

R. Kumar and A. Patel,
"Deep Learning Model for Weather Forecasting Using LSTM,"
2021 3rd International Conference on Signal Processing and Communication (ICPSC), Coimbatore, India, 2021, pp. 393–398,

P. Bhasme, J. Vagadiya, and U. Bhatia,
"Physics-Informed Machine Learning for Hydrological Processes in Data-Scarce Regions,"
Journal of Hydrology, vol. 609, Part A, 2022, 127713.

H. Yang, D. Tian, and L. Li,
"A Hybrid LSTM Model Integrated with HEC-HMS for Runoff Forecasting,"
Frontiers in Environmental Science, vol. 11, 2023, Article 1261239.

Y. Zhang, F. Chen, and Y. Wang,
"A Three-Stage Hybrid Modeling Strategy for Real-Time Streamflow Prediction,"
Environmental Advances, vol. 13, 2025, Article 100344.

· Xin, X.-F., & He, S. Y.
Pseudomonas syringae: what it takes to be a pathogen.
Molecular Plant Pathology, vol. 14, no. 7, 2013, pp. 1–11.

· · Yu, X., Lund, S. P., Scott, R. A., Greenwald, J. W., Records, A. H., Nettleton, D., Lindow, S. E., Gross, D. C., & Beattie, G. A.
Transcriptional responses of Pseudomonas syringae to growth in epiphytic versus apoplastic leaf sites.
Proceedings of the National Academy of Sciences, vol. 110, no. 5, 2013, pp. E425–E434.

López-Pagán, N., Rufián, J. S., Luneau, J., Sánchez-Romero, M.-A., Aussel, L., van Vliet, S., Ruiz-Albert, J., & Beuzón, C. R.
Pseudomonas syringae subpopulations cooperate by coordinating the biosynthesis of a diffusible factor.
Nature Microbiology, vol. 10, 2025, pp. 958–972.

·Hulin, M. T., Armitage, A. D., Vicente, J. G., & Jackson, R. W.
Genomic characterization of Pseudomonas syringae pv. syringae and its bacteriophages isolated from ornamental pear trees.
Microbiology Spectrum, vol. 11, no. 2, 2023.

Mansfield, J., Genin, S., Magori, S., Citovsky, V., Sriariyanum, M., Ronald, P., Dow, M., Verdier, V., Beer, S. V., Machado, M. A., Toth, I., Salmond, G., & Foster, G. D.
Top 10 plant pathogenic bacteria in molecular plant pathology.
Molecular Plant Pathology, vol. 13, no. 6, 2012, pp. 614–629.

Beattie, G. A.
Water relations in the interaction of foliar bacterial pathogens with plants.
Annual Review of Phytopathology, vol. 49, 2011, pp. 533–555.

Hatfield, B. M., LaSarre, B., Liu, M., Dong, H., Nettleton, D., & Beattie, G. A.
Light cues induce protective anticipation of environmental water loss in terrestrial bacteria.
Proceedings of the National Academy of Sciences, vol. 120, no. 39, 2023, e2306018120.

H. Yang, D. Tian, and L. Li,
"A Hybrid Rainfall-Runoff Model: Integrating Initial Loss and LSTM for Improved Hydrological Modeling,"
Frontiers in Environmental Science, vol. 11, 2023, Article 1261239.

Y. Zhang, F. Chen, and Y. Wang,
"A Three-Stage Hybrid Modeling Strategy for Real-Time Streamflow Prediction in Data-Limited Regions,"
Environmental Advances, vol. 13, 2025, Article 100344.

P. Bhasme, J. Vagadiya, and U. Bhatia,
"Physics-Informed Machine Learning for Hydrological Processes in Data-Scarce Regions,"
Journal of Hydrology, vol. 609, Part A, 2022, 127713.

M. T. Hulin, A. D. Armitage, J. G. Vicente, and R. W. Jackson,
"Genomic Characterization of Pseudomonas syringae pv. syringae and Its Bacteriophages Isolated from Ornamental Pear Trees,"
Microbiology Spectrum, vol. 11, no. 2, 2023.

J. Mansfield et al.,
"Top 10 Plant Pathogenic Bacteria in Molecular Plant Pathology,"
Molecular Plant Pathology, vol. 13, no. 6, 2012, pp. 614–629.

G. A. Beattie,
"Water Relations in the Interaction of Foliar Bacterial Pathogens with Plants,"
Annual Review of Phytopathology, vol. 49, 2011, pp. 533–555.

B. M. Hatfield et al.,
"Light Cues Induce Protective Anticipation of Environmental Water Loss in Terrestrial Bacteria,"
Proceedings of the National Academy of Sciences, vol. 120, no. 39, 2023, e2306018120.

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