AI-Powered Precipitation Prediction System for Small-Scale Farmers

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04.08.2024

Abstract

This paper presents an AI-powered precipitation system system designed to support small-scale farmers. The system aims to address the challenges posed by unpredictable weather, which significantly affects crop yields and financial stability. Using advanced machine learning algorithms, the system integrates real-time weather data from local stations, satellite feeds and historical records to provide accurate and timely rainfall forecasts. This predictive capability allows farmers to make informed decisions about irrigation, planting and harvesting, thereby optimizing resource use and minimizing risk. The proposed solution is designed to be cost-effective and user-friendly to meet the specific needs of small-scale farmers who typically do not have access to sophisticated weather forecasting tools. The article outlines the system development process, including data sources, algorithms, and the team required for implementation. It also discusses potential business models for monetization, such as a freemium model offering basic predictions for free with premium features available via subscription. By providing farmers with reliable weather forecasts, this AI-driven system aims to increase agricultural productivity and sustainability.

1. Problem Statement

Small-scale farmers often face significant challenges due to unpredictable weather patterns, which can result in poor crop yields and financial losses. Accurate precipitation prediction is essential for these farmers to plan their agricultural activities effectively. The core problem involves enhancing agricultural productivity and sustainability through the integration of Artificial Intelligence (AI). Key issues include unpredictable weather patterns, as traditional forecasting methods are often inadequate for precise agricultural planning. This inadequacy leads to challenges such as improper irrigation scheduling and inefficient resource use, negatively affecting crop yields and farmer income. Additionally, many current irrigation systems are inefficient, lacking the capability to adapt in real-time to changing weather conditions and soil moisture levels, which can cause water wastage or insufficient watering, thereby harming crop health and productivity. Another issue is the limited utilization of available data, as there is often a gap between meteorological data and its practical application in agriculture, leading to suboptimal farming practices. Furthermore, technology accessibility is a challenge, as small-scale and resource-limited farmers may find it difficult to access advanced AI and IoT technologies, which are typically designed for larger operations, creating a disparity in the adoption of technologies that could enhance farming efficiency and resilience. Addressing these issues requires the development of AI-powered solutions that offer accurate, real-time weather predictions, optimize irrigation systems, and are accessible to farmers of all scales.

2. Market/Customer/Business Need Assessment

2.1 Market Assessment

The target market for the AI-powered precipitation prediction system includes small-scale farmers primarily located in rural and semi-rural areas, with a focus on regions heavily reliant on agriculture and experiencing variable weather patterns. The global AI in agriculture market is expanding, with significant investments in precision farming technologies, indicating a strong market potential for AI-powered weather prediction systems specifically designed for small-scale farmers.

2.2 Customer Characteristics

The primary customers are small-scale farmers who often have limited access to advanced agricultural technologies, relying on traditional farming methods and basic weather forecasts. These farmers need cost-effective and user-friendly solutions to enhance their farming practices. They face several challenges, including limited financial and technological resources, a high dependency on accurate weather forecasts for critical decision-making, and a limited ability to leverage meteorological data effectively.

2.3 Business Need

The business need for an AI-powered precipitation prediction system for small-scale farmers includes providing precise and localized weather forecasts to improve planning and resource allocation, helping farmers optimize irrigation schedules based on accurate precipitation predictions, thereby conserving water and enhancing crop yields. Additionally, developing affordable AI-powered tools that small-scale farmers can easily access and use is crucial. A freemium model can be implemented where basic weather predictions are free, with premium features like detailed analysis and personalized alerts available through subscription. Moreover, offering training and support to help farmers understand and utilize these systems, and ensuring the interface is simple and user-friendly, will encourage adoption among farmers with varying levels of technological proficiency.

2.4 Competitive Landscape

The competitive landscape for AI-powered precipitation prediction systems reveals that existing solutions are primarily designed for large-scale farming operations, leaving a market gap for tools tailored to small-scale farmers. Competitors include agritech startups and established companies offering precision agriculture tools. The unique selling proposition of this system lies in its focus on accessibility, affordability, and ease of use for small-scale farmers. By integrating localized weather data with machine learning algorithms, it aims to provide highly accurate and relevant forecasts, meeting the specific needs of small-scale agricultural operations.

3. Target Specifications and Characterization

3.1 Target Specifications:

a) **Accuracy**:

- Provide highly accurate and localized weather forecasts.
- Use machine learning algorithms to improve prediction accuracy over time.

b) **Data Integration**:

- Collect and process data from various sources, including local weather stations, satellite data, and historical weather records.
- Use smart weather data management to ensure precision and sustainability in agriculture.

c) **User-Friendly Interface**:

- Develop a simple and intuitive interface for farmers with varying levels of technological proficiency.
- Ensure the system is accessible via mobile app and web platform to accommodate different user preferences and connectivity levels.

d) **Cost-Effective**:

- Implement a freemium model with basic weather predictions available for free.
- Offer premium features like detailed analysis and personalized alerts through affordable subscriptions.

e) **Resource Optimization**:

- Help farmers optimize irrigation schedules based on accurate precipitation predictions to conserve water and enhance crop yields.
- Provide recommendations on optimal planting times and crop health monitoring.

3.2 Characterization:

a) Customer Characteristics:

- Small-scale farmers in rural and semi-rural areas with limited access to advanced agricultural technologies.

- Farmers who rely on traditional methods and basic weather forecasts, needing cost-effective and user-friendly solutions.

b) Geographic Focus:

- Target regions heavily reliant on agriculture with variable weather patterns.
- Areas where accurate weather forecasting can significantly impact agricultural productivity and sustainability.

c) Technical Specifications:

- Utilize AI models like convolutional neural networks (CNNs) and long short-term memory (LSTM) for weather pattern recognition and prediction.
- Ensure the system supports real-time data processing and delivers timely updates to users.

4. External Search

i. Research on AI Applications in Agriculture:

Recent advancements in AI have significantly impacted agriculture, enabling more accurate weather predictions and better resource management. AI can help farmers choose the optimal time to plant seeds, calculate spacing, and determine planting depth. AI-based systems can also monitor soil moisture, air quality, and provide real-time weather updates to assist in making informed decisions.

ii. Practical AI Applications in Farming:

AI-based crop recommendation systems and intelligent agriculture management systems use data analysis to optimize farming practices and improve crop yields. These systems utilize machine learning algorithms to analyse data on precipitation, river flow, and groundwater levels to predict future water availability. This approach helps in precision agriculture by improving overall crop harvest quality and accuracy.

iii. Benchmarking Alternate Products:

Most existing AI-powered weather forecasting tools cater to large-scale farming operations. Solutions like IBM's Watson Decision Platform for Agriculture offer advanced AI-driven weather predictions but are often not tailored for small-scale farmers. These tools provide functionalities such as creating digital maps of fields, detecting crop health issues, and managing weather data for sustainability and precision.

iv. Existing Solutions:

Competitors in this space include agritech startups and established companies that provide precision agriculture tools. Current solutions often overlook the specific needs of small-scale farmers, creating a gap in the market for more accessible and affordable tools tailored to this segment. By focusing on localized weather data and user-friendly interfaces, our AI-powered precipitation prediction system aims to bridge this gap and provide highly accurate and relevant forecasts for small-scale farmers.

5. Benchmarking Alternate Products

- **Existing AI-Powered Weather Forecasting Tools:**
    - Current AI systems can forecast weather patterns, assess crop health, and detect diseases or pests, providing comprehensive support for large-scale farming operations. These tools often involve sophisticated AI algorithms and extensive datasets to deliver precise predictions and actionable insights.
    - AI-powered systems like the one developed by Benchmark Labs offer personalized weather forecasts to enhance crop yields. These solutions use machine learning to process meteorological data, including temperature, humidity, rainfall, and wind patterns, to predict weather conditions accurately.
- **Health Monitoring and Precision Agriculture:**
    - AI-based health monitoring systems provide farmers with critical information on crop health and nutrient status, enabling precise interventions. These systems are designed to optimize resource usage and improve productivity, primarily catering to precision agriculture.
    - Intelligent agriculture management systems monitor soil moisture and air quality, helping farmers make informed decisions about irrigation and other farming practices. These systems often use cloud computing and IoT devices to collect and analyze data in real-time.
- **Robotic and Autonomous Solutions:**
    - Some AI implementations involve robotic systems performing tasks like weeding, irrigation, and guarding farms autonomously. These solutions provide effective monitoring and reporting, ensuring that farming operations are conducted efficiently and sustainably.
    - AI algorithms process vast amounts of meteorological data to predict weather conditions accurately, which is crucial for planning and optimizing farming activities.

6. Applicable Patents

 Weather Prediction Models:

- **Patent US10274272B2** - This patent covers methods for predicting weather patterns using machine learning models, including convolutional neural networks (CNNs) and recurrent neural networks (RNNs). These methods are integral for developing accurate precipitation forecasts based on historical weather data and real-time inputs.

 AI-Based Agricultural Forecasting:

- **Patent US10734610B2** - Focuses on using AI to provide agricultural forecasts. It involves integrating various data sources such as meteorological data, soil conditions, and crop health to optimize agricultural practices. This patent is relevant for creating models that predict weather impacts on farming.

 IoT and Cloud Computing for Agriculture:

- **Patent US10334476B2** - Describes systems for integrating IoT devices and cloud computing to monitor and analyse agricultural conditions, including weather forecasts. This technology is crucial for developing a real-time weather prediction system that utilizes data from multiple sensors and weather stations.

 Personalized Weather Forecasting Systems:

- **Patent US10848229B2** - Pertains to systems providing personalized weather forecasts based on user-specific needs and local conditions. This patent supports the creation of user-centric weather prediction tools that small-scale farmers can use for precise agricultural planning.

 Precision Agriculture and Data Integration:

- **Patent US10626000B2** - Covers technologies for integrating precision agriculture data with weather prediction models. It includes methods for processing meteorological and agricultural data to enhance predictive accuracy and support decision-making for farmers.

7. Applicable Regulations

 Data Privacy Regulations:

- **General Data Protection Regulation (GDPR):** In the European Union, GDPR governs the collection and processing of personal data. It requires obtaining explicit consent from users before collecting their data and ensuring the secure storage and handling of this data.

Although not directly related to precipitation prediction, if personal data is involved, compliance is essential.

- **California Consumer Privacy Act (CCPA):** In California, the CCPA mandates transparency about data collection practices and gives users the right to access, delete, and opt-out of the sale of their personal data. Compliance with CCPA is crucial if the system collects or processes personal data from users in California.

 Agricultural Regulations:

- **Food Safety and Inspection Service (FSIS) Regulations:** While FSIS primarily deals with food safety, any technology impacting agriculture must comply with regulations concerning food safety standards if the system affects food crops directly.
- **Pesticide Regulation Compliance:** If the system's recommendations impact pesticide use, it must adhere to regulations set by bodies like the Environmental Protection Agency (EPA) in the U.S., which governs the use of pesticides in agriculture.

 Technology and AI Regulations:

- **AI Ethics Guidelines:** Many countries are developing guidelines for the ethical use of AI, including transparency, fairness, and accountability. The European Commission, for example, has proposed regulations focusing on ensuring that AI systems are used responsibly and do not lead to unintended consequences or biases.
- **Software Compliance Standards:** Adherence to standards for software development and deployment, including cybersecurity practices, is necessary to protect against data breaches and ensure the system's reliability and security.

 Environmental Regulations:

- **National Environmental Policy Act (NEPA):** In the U.S., NEPA requires environmental assessments for projects that may significantly impact the environment. If the system's recommendations influence environmental practices, such as irrigation or land use, an assessment may be required.

8. Applicable Constraints

 Cost Constraints:

- **High Initial Costs:** Implementing AI and IoT technologies can involve significant upfront expenses. For small-scale farmers, these costs may be prohibitive, affecting the affordability and adoption of such systems.

 Technology Accessibility:

- **Limited Internet Connectivity:** Rural areas often face challenges with stable and high-speed internet, which is crucial for real-time data transmission and AI model updates.
- **Technical Skill Requirements:** Small-scale farmers may lack the technical expertise to effectively utilize advanced AI tools, necessitating user-friendly interfaces and support systems.

 Data Accuracy and Integration:

- **Data Quality:** AI systems depend on accurate and comprehensive weather data. Inconsistent or poor-quality data can lead to inaccurate predictions.
- **Integration with Existing Systems:** Compatibility with existing agricultural practices and technologies is essential for seamless adoption. The system must be adaptable to various farming methods and tools.

 Scalability Issues:

- **System Scalability:** Ensuring that the AI solution can scale to different farm sizes and types without compromising performance or accuracy is crucial.

9. Business Model (Monetization Idea)

 Freemium Model:

- **Basic Access:** Provide a free tier offering essential precipitation forecasts and general weather insights. This attracts a broad user base and introduces them to the system.
- **Premium Features:** Offer advanced functionalities such as detailed weather analytics, personalized alerts, and historical data insights through a subscription model. Premium users could also receive additional support and consultancy services.

 Subscription-Based Model:

- **Monthly/Annual Subscriptions:** Charge users a recurring fee for access to comprehensive features. Different tiers could offer varying levels of detail and additional services like expert consultations and customized forecasts.

 Pay-Per-Use Model:

- **On-Demand Reports:** Allow farmers to pay for individual reports or detailed weather forecasts on an as-needed basis. This model can be attractive for users who prefer to pay only when they need specific insights.

 Advertising and Partnerships:

- **In-App Advertising:** Integrate relevant advertisements from agricultural suppliers, equipment manufacturers, or local service providers. Ensure ads are non-intrusive and relevant to the farmers' needs.
- **Partnerships:** Collaborate with agricultural organizations, local governments, or NGOs that focus on farming support. These partners can subsidize costs for farmers or offer the system as part of a larger support package.

 Data and Insights Sales:

- **Aggregated Data:** Sell anonymized, aggregated weather data and insights to research institutions, agricultural agencies, or commercial entities interested in market trends and agricultural patterns.

10. Concept Generation

The AI-powered precipitation prediction system is designed to provide small-scale farmers with precise and actionable weather forecasts, specifically focusing on precipitation. The concept revolves around leveraging artificial intelligence and machine learning to enhance weather prediction accuracy, which is crucial for optimizing agricultural practices.

a) **Data Collection and Integration:** The system collects data from multiple sources, including local weather stations, satellite imagery, and historical weather records. This diverse data pool allows for a comprehensive analysis of weather patterns.
b) **AI and Machine Learning Models:** Advanced machine learning algorithms, such as Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks, are used to process and analyse the collected data. These models are trained to recognize patterns and predict precipitation levels with high accuracy.
c) **User Interface:** The system is accessible through a mobile app and a web platform, ensuring ease of use for farmers in both remote and semi-urban areas. The interface provides real-time precipitation forecasts, personalized weather alerts, and historical data trends.
d) **Practical Applications:** Farmers can use these predictions to plan irrigation schedules, manage crop protection measures, and optimize planting and harvesting times. This leads to more efficient water use, reduced crop loss, and improved yields.
e) **Accessibility and Affordability:** To ensure widespread adoption, the system will be designed to be cost-effective and user-friendly. A freemium model can be employed, where basic forecasts are free, and advanced features are available through a subscription.
f) **Validation and Testing:** Before full deployment, the system will undergo rigorous testing to validate its accuracy and reliability. Pilot programs in selected regions will help refine the models and ensure that the system meets the needs of small-scale farmers.

This AI-powered precipitation prediction system aims to empower small-scale farmers by providing them with actionable insights into weather patterns, ultimately leading to improved agricultural outcomes and sustainable practices.

11. Concept Development

The development of an AI-powered precipitation prediction system for small-scale farmers involves several key steps:

a. Data Collection and Integration: To build a robust predictive system, diverse data sources are utilized, including weather station data, satellite imagery, and historical weather records. This comprehensive data collection helps capture various weather patterns and anomalies that affect precipitation.

b. AI and Machine Learning Algorithms: The core of the system is the AI model, which employs advanced machine learning techniques such as Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks. These algorithms process and analyse the collected data to generate accurate precipitation forecasts. The models are trained on historical data to recognize patterns and predict future weather conditions.

c. User Interface Development: The system is accessible through a user-friendly mobile app and web platform, ensuring ease of use for farmers. The interface provides real-time weather updates, personalized alerts, and historical weather trends. It is designed to be intuitive, even for users with limited technological experience.

d. Integration with Farming Practices: The predictions are used to optimize various farming practices, including irrigation scheduling and crop protection. By integrating these forecasts into daily farming decisions, the system helps farmers manage resources more effectively, reducing waste and improving crop yields.

e. Testing and Validation: The system undergoes rigorous testing to ensure accuracy and reliability. Pilot programs in different regions allow for adjustments based on real-world data and feedback from farmers. This phase is crucial for refining the system and confirming its effectiveness in various environmental conditions.

f. Accessibility and Cost Considerations: To ensure that the system is accessible to small-scale farmers, it will be designed with affordability in mind. A freemium model can be implemented, where basic features are free, and advanced functionalities are available through a subscription. This approach helps in balancing cost and accessibility.

This AI-powered precipitation prediction system aims to enhance agricultural productivity and sustainability by providing small-scale farmers with precise and actionable weather forecasts.

12. Final Product Prototype (Abstract) with Schematic Diagram

Prototype Overview:

The final product prototype for the AI-powered precipitation prediction system integrates several components to provide accurate and actionable weather forecasts to small-scale farmers. This system is designed to improve farming decisions and optimize resource usage.

Key Components:

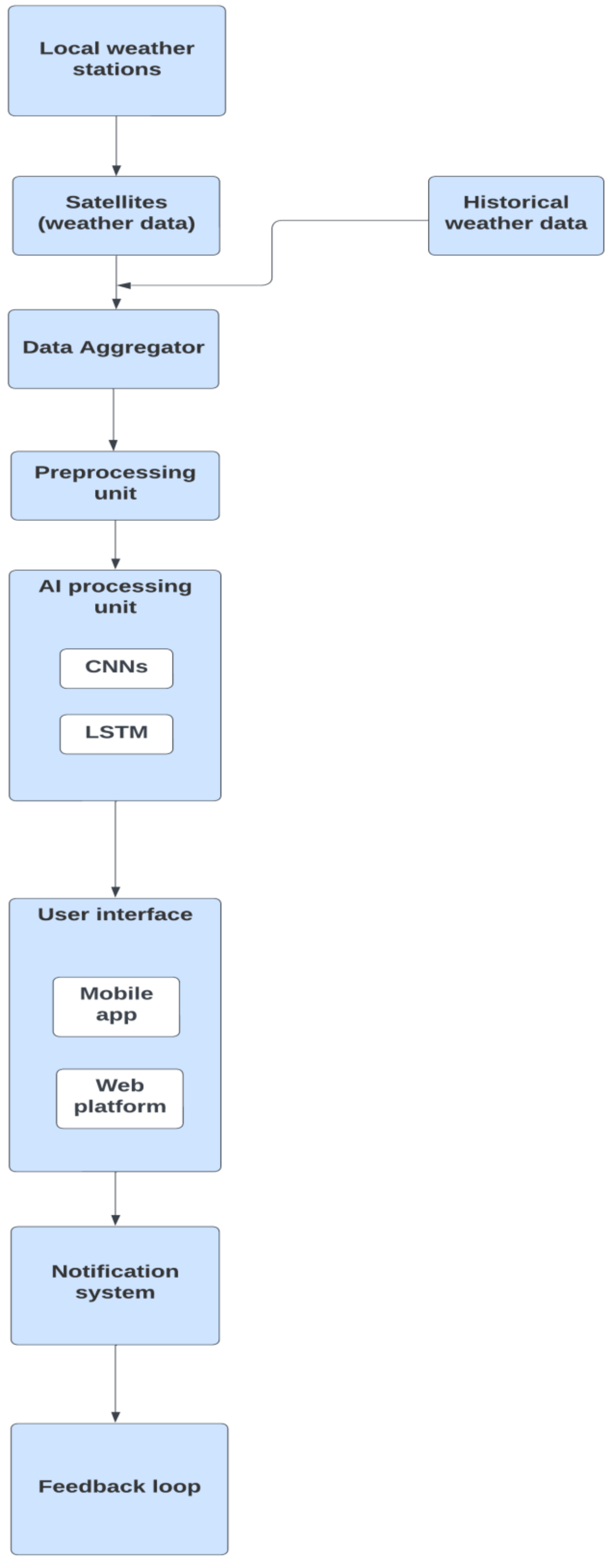
I. **Data Collection Module:**
   - **Sensors:** Collect real-time data from local weather stations and satellites.
   - **Historical Data:** Incorporates historical weather records to enhance forecast accuracy.

II. **AI Processing Unit:**
   - **Machine Learning Models:** Employ Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks to analyse weather patterns and predict precipitation.
   - **Data Fusion:** Integrates data from various sources to provide comprehensive weather predictions.

III. **User Interface:**
   - **Mobile Application:** Delivers real-time precipitation forecasts, alerts, and historical weather data.
   - **Web Platform:** Provides detailed weather analysis and additional features for comprehensive insights.

IV. **Notification System:**
   - **Alerts:** Sends notifications via the app or email to update farmers about significant weather changes and recommendations.

Schematic Diagram:



The schematic diagram shows the flow of data from collection through processing to user delivery. It illustrates how weather data is gathered, analysed by AI models, and presented to users via the mobile app and web platform.

13. Product Details

13.1. How It Works

The AI-powered precipitation prediction system integrates various data sources and advanced machine learning algorithms to provide accurate and actionable weather forecasts. The system operates through several key steps:

a) **Data Collection:**

- **Local Weather Stations:** Collect real-time weather data including temperature, humidity, and precipitation.
- **Satellites:** Provide large-scale weather data and high-resolution satellite imagery.
- **Historical Weather Data:** Past weather records are used to analyze trends and patterns.

b) **Data Integration and Preprocessing:**

- **Data Aggregator:** Gathers and combines real-time data from local weather stations and satellites with historical data.
- **Preprocessing Unit:** Cleans and normalizes the collected data to prepare it for analysis.

c) **AI Processing:**

- **Machine Learning Models:**
  - **Convolutional Neural Networks (CNNs):** Analyze spatial data from satellite imagery to detect weather patterns.
  - **Long Short-Term Memory (LSTM) Networks:** Manage temporal data to predict future precipitation based on historical and current weather patterns.
- **Data Fusion Engine:** Integrates the outputs of different models to provide a refined and accurate precipitation forecast.

d) **User Interface:**

- **Mobile Application:**
  - **Forecast Dashboard:** Provides real-time and forecasted precipitation data, weather conditions, and trends.
  - **Alerts & Notifications:** Sends push notifications and alerts based on significant weather changes or predictions.
- **Web Platform:**
  - **Detailed Analysis:** Offers in-depth weather analysis, including graphs, historical comparisons, and detailed forecast data.

e) **Notification System:**

- **Alert System:** Delivers notifications via the mobile app and email to keep farmers informed of important weather updates.

f) **Feedback Loop:**

- **User Input:** Allows farmers to provide feedback on forecast accuracy and system performance.
- **System Adjustment:** Uses user feedback to continuously improve AI models and system functionality.

13.2. Data Sources

- **Local Weather Stations:** Provide real-time, localized weather information.
- **Satellites:** Supply broad, high-resolution weather and atmospheric data.
- **Historical Weather Records:** Offer context and trends for better prediction accuracy.

13.3. Algorithms

- **Convolutional Neural Networks (CNNs):** Used for analyzing spatial features in satellite imagery.
- **Long Short-Term Memory (LSTM) Networks:** Applied to predict temporal changes in weather patterns based on historical and current data.

13.4. Team Required

- **Data Scientists:** Develop and refine machine learning models and algorithms.

- **Software Developers:** Build and maintain the mobile app and web platform.
- **Agricultural Experts:** Provide insights into farming needs and ensure the system's relevance to small-scale farmers.

13.5. Cost

- **Development Costs:** Includes expenses for data acquisition, algorithm development, and software engineering.
- **Subscription Fees:** Freemium model with basic features available for free, and premium features (e.g., detailed analysis, personalized alerts) available through subscription.

14. Code Implementation

```
#importing data
import pandas as pd
df=pd.read_csv('dataset.csv')
print(df)
```

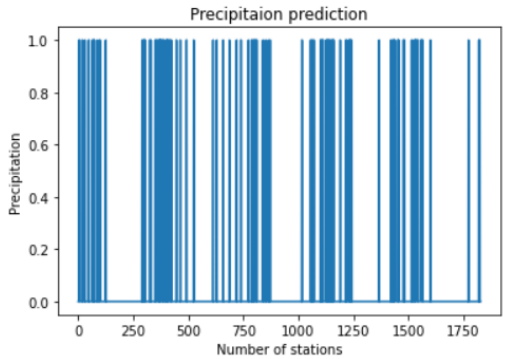
```
          STATION                             NAME        DATE  AWND  PGTM  \
0     USW00093134  LOS ANGELES DOWNTOWN USC, CA US  2016-01-01  2.46   NaN
1     USW00093134  LOS ANGELES DOWNTOWN USC, CA US  2016-01-02  2.01   NaN
2     USW00093134  LOS ANGELES DOWNTOWN USC, CA US  2016-01-03  0.67   NaN
3     USW00093134  LOS ANGELES DOWNTOWN USC, CA US  2016-01-04  1.34   NaN
4     USW00093134  LOS ANGELES DOWNTOWN USC, CA US  2016-01-05  2.46   NaN
...           ...                              ...         ...   ...   ...
1822  USW00093134  LOS ANGELES DOWNTOWN USC, CA US  2020-12-27  1.12   NaN
1823  USW00093134  LOS ANGELES DOWNTOWN USC, CA US  2020-12-28  4.70   NaN
1824  USW00093134  LOS ANGELES DOWNTOWN USC, CA US  2020-12-29  1.57   NaN
1825  USW00093134  LOS ANGELES DOWNTOWN USC, CA US  2020-12-30  0.45   NaN
1826  USW00093134  LOS ANGELES DOWNTOWN USC, CA US  2020-12-31  1.57   NaN

      PRCP  TAVG  TMAX  TMIN   WDF2   WDF5  WSF2  WSF5  WT01  WT02  WT08
0     0.00   NaN    64    43   10.0   30.0   8.1  11.0   NaN   NaN   1.0
1     0.00   NaN    65    47  270.0   30.0   6.0   8.9   NaN   NaN   NaN
2     0.00   NaN    62    44  150.0  150.0  10.1  14.1   NaN   NaN   NaN
3     0.01   NaN    69    55  270.0  280.0   8.1  14.1   NaN   NaN   NaN
4     1.61   NaN    59    49  140.0  140.0  10.1  16.1   1.0   1.0   NaN
...    ...   ...   ...   ...    ...    ...   ...   ...   ...   ...   ...
1822  0.01   NaN    66    55  270.0  260.0   8.9  18.1   1.0   NaN   1.0
1823  1.81   NaN    56    47   90.0  260.0  14.1  21.0   1.0   NaN   NaN
1824  0.00   NaN    65    42  340.0  360.0  10.1  18.1   NaN   NaN   NaN
1825  0.00   NaN    69    44  260.0  260.0   6.9  12.1   NaN   NaN   NaN
1826  0.00   NaN    70    43  350.0  350.0  12.1  19.9   NaN   NaN   NaN

[1827 rows x 16 columns]
```

```
# replacing all PRCP values greater than 0 as 1
df.loc[df['PRCP']>0,'PRCP']=1
print(df)
```

```
%matplotlib inline
from matplotlib import pyplot as plt
import pandas as pd
plt.plot(df['PRCP'])
plt.title('Precipitaion prediction')
plt.xlabel('Number of stations')
plt.ylabel('Precipitation')
plt.show()
```




```
from sklearn.utils import resample,shuffle
df_1 = df[df['PRCP'] == 1]
other_df = df[df['PRCP'] == 0]
#upsample the minority class
df_1_upsampled = resample(df_1,random_state=None,n_samples=None,replace=True)
#concatenate the upsampled dataframe
df_upsampled = pd.concat([df_1_upsampled,other_df])
df_upsampled
```

	STATION	NAME	DATE	AWND	PGTM	PRCP	TAVG	TMAX	TMIN	WDF2	WDF5	WSF2	WSF5	WT01	WT02	WT08
369	USW00093134	LOS ANGELES DOWNTOWN USC, CA US	2017-01-04	1.12	NaN	1.0	NaN	63	47	90.0	100.0	8.1	13.0	1.0	NaN	1.0
1154	USW00093134	LOS ANGELES DOWNTOWN USC, CA US	2019-02-28	2.68	NaN	1.0	NaN	67	56	260.0	280.0	6.9	11.0	1.0	NaN	1.0
1822	USW00093134	LOS ANGELES DOWNTOWN USC, CA US	2020-12-27	1.12	NaN	1.0	NaN	66	55	270.0	260.0	8.9	18.1	1.0	NaN	1.0
1153	USW00093134	LOS ANGELES DOWNTOWN USC, CA US	2019-02-27	1.34	NaN	1.0	NaN	66	50	270.0	270.0	8.9	15.0	1.0	NaN	1.0
1822	USW00093134	LOS ANGELES DOWNTOWN USC, CA US	2020-12-27	1.12	NaN	1.0	NaN	66	55	270.0	260.0	8.9	18.1	1.0	NaN	1.0
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
1820	USW00093134	LOS ANGELES DOWNTOWN USC, CA US	2020-12-25	1.57	NaN	0.0	NaN	75	52	270.0	270.0	8.9	14.1	NaN	NaN	NaN
1821	USW00093134	LOS ANGELES DOWNTOWN USC, CA US	2020-12-26	0.67	NaN	0.0	NaN	69	46	260.0	250.0	6.9	12.1	NaN	NaN	NaN
1824	USW00093134	LOS ANGELES DOWNTOWN USC, CA US	2020-12-29	1.57	NaN	0.0	NaN	65	42	340.0	360.0	10.1	18.1	NaN	NaN	NaN
1825	USW00093134	LOS ANGELES DOWNTOWN USC, CA US	2020-12-30	0.45	NaN	0.0	NaN	69	44	260.0	260.0	6.9	12.1	NaN	NaN	NaN
1826	USW00093134	LOS ANGELES DOWNTOWN USC, CA US	2020-12-31	1.57	NaN	0.0	NaN	70	43	350.0	350.0	12.1	19.9	NaN	NaN	NaN

```python
#dropping features with many null values
df=df[df.columns[df.isnull().mean() < 0.01]]
```

```python
#converting the rest of the null values with mode
df['AWND'] = df['AWND'].fillna(df['AWND'].mode()[0])
df['PRCP'] = df['PRCP'].fillna(df['PRCP'].mode()[0])
df['TMAX'] = df['TMAX'].fillna(df['TMAX'].mode()[0])
df['TMIN'] = df['TMIN'].fillna(df['TMIN'].mode()[0])
df['WDF2'] = df['WDF2'].fillna(df['WDF2'].mode()[0])
df['WDF5'] = df['WDF5'].fillna(df['WDF5'].mode()[0])
df['WSF2'] = df['WSF2'].fillna(df['WSF2'].mode()[0])
df['WSF5'] = df['WSF5'].fillna(df['WSF5'].mode()[0])
```

```python
#normalizing data
import numpy as np
import seaborn as sns
from sklearn.preprocessing import LabelEncoder

label_encoder = LabelEncoder()
df['STATION'] = label_encoder.fit_transform(df['STATION'])
df['NAME'] = label_encoder.fit_transform(df['NAME'])
df['DATE'] = label_encoder.fit_transform(df['DATE'])
df.head()
```

	STATION	NAME	DATE	AWND	PRCP	TMAX	TMIN	WDF2	WDF5	WSF2	WSF5
0	0	0	0	2.46	0.0	64	43	10.0	30.0	8.1	11.0
1	0	0	1	2.01	0.0	65	47	270.0	30.0	6.0	8.9
2	0	0	2	0.67	0.0	62	44	150.0	150.0	10.1	14.1
3	0	0	3	1.34	1.0	69	55	270.0	280.0	8.1	14.1
4	0	0	4	2.46	1.0	59	49	140.0	140.0	10.1	16.1

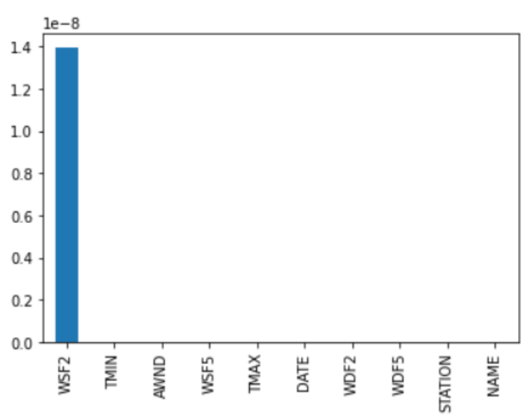
```python
from sklearn.feature_selection import chi2

X = df.drop('PRCP',axis=1)
y = df['PRCP']
scores = chi2(X,y)
scores
```

```
(array([          nan,           nan,  845.54850795,   79.05899558,
         318.33894152,   54.00341786, 2310.12947627, 1828.05882977,
          32.19213439,   83.73695329]),
 array([           nan,              nan, 6.75045568e-186, 6.02826182e-019,
        3.33210470e-071, 2.00141159e-013, 0.00000000e+000, 0.00000000e+000,
        1.39654983e-008, 5.65188246e-020]))
```

```python
p_values = pd.Series(scores[1],index = X.columns)
p_values.sort_values(ascending = False , inplace = True)
p_values.plot.bar()
```

```
<AxesSubplot:>
```



```python
#Splitting data into test and train datasets
from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.25, random_state=0)
```

```python
# make class predictions for the testing set
from sklearn.linear_model import LogisticRegression
logreg = LogisticRegression(max_iter=3000).fit(X_train,y_train)
y_pred_class = logreg.predict(X_test)
```

```python
# calculate accuracy
from sklearn import metrics
print(metrics.accuracy_score(y_test, y_pred_class))
```

```
0.936542669584245
```

```python
# calculate precision
print(metrics.precision_score(y_test, y_pred_class))
```

```
0.6818181818181818
```

```python
# calculate recall
print(metrics.recall_score(y_test, y_pred_class))
```

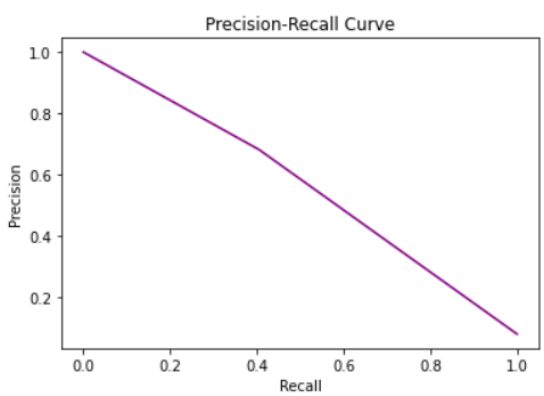
```
0.40540540540540543
```

```python
from sklearn.metrics import precision_recall_curve
#calculate precision and recall
precision, recall, thresholds = precision_recall_curve(y_test, y_pred_class)

#create precision recall curve
fig, ax = plt.subplots()
ax.plot(recall, precision, color='purple')

#add axis labels to plot
ax.set_title('Precision-Recall Curve')
ax.set_ylabel('Precision')
ax.set_xlabel('Recall')

#display plot
plt.show()
```



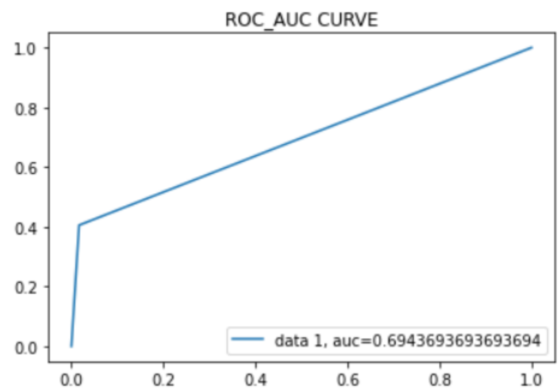
```python
# calculate F-1 score
print(metrics.f1_score(y_test, y_pred_class))
```

```
0.5084745762711864
```

```python
# calculate ROC_AUC
print(metrics.roc_auc_score(y_test, y_pred_class))
```

```
0.6943693693693694
```

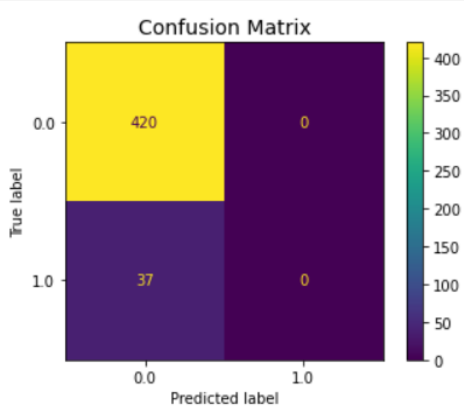
```python
fpr, tpr, _ = metrics.roc_curve(y_test,  y_pred_class)
auc = metrics.roc_auc_score(y_test, y_pred_class)
plt.plot(fpr,tpr,label="data 1, auc="+str(auc))
plt.legend(loc=4)
plt.title('ROC_AUC CURVE', fontsize=12)
plt.show()
```




```python
print(metrics.confusion_matrix(y_test, y_pred_class))
```

```
[[413   7]
 [ 22  15]]
```

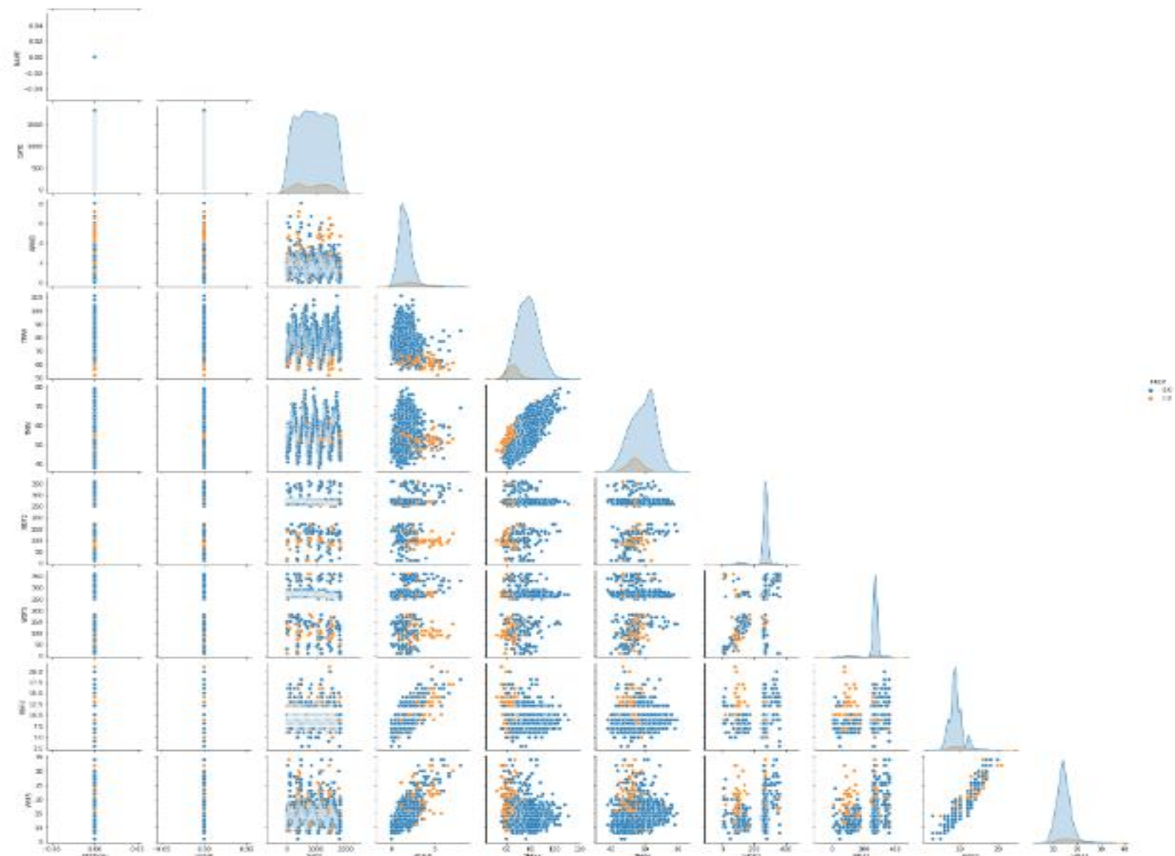
```python
from sklearn.datasets import make_classification
from sklearn.metrics import plot_confusion_matrix
from sklearn.svm import SVC
X, y = make_classification(random_state=0)
clf = SVC(random_state=0)
clf.fit(X_train, y_train)
SVC(random_state=0)
plot_confusion_matrix(clf, X_test, y_test)
plt.title('Confusion Matrix', fontsize=14)
plt.show()
```



```
#visualizing using seaborn
import seaborn as sns

sns.pairplot(df.iloc[:, :], hue='PRCP', corner=True)
```

```
<seaborn.axisgrid.PairGrid at 0x253831c7ca0>
```



15. Conclusion

The AI-powered precipitation prediction system represents a transformative solution for small-scale farmers, addressing critical challenges posed by unpredictable weather. By leveraging advanced machine learning models and integrating various data sources, this system provides highly accurate and actionable weather forecasts. The key benefits and outcomes include enhanced decision-making, where farmers receive precise predictions on precipitation to make informed decisions about planting, irrigation, and harvesting, thus optimizing resource use and improving crop yields. Improved risk management is achieved through timely and accurate forecasts that help mitigate risks associated with extreme weather, reducing potential financial losses and enhancing overall farm resilience. The system features a user-friendly interface with mobile and web platforms designed for ease of use, delivering real-time updates and alerts in accessible formats even in areas with limited technical infrastructure. Ongoing improvement is ensured through the incorporation of user feedback and continuous learning algorithms, which evolve the system to meet changing needs and enhance prediction accuracy over time. Overall, this AI-powered system equips small-scale farmers with essential tools to navigate modern agriculture complexities, promoting more sustainable and productive farming practices.

🌐 References

- **AI-Based Real-Time Weather Condition Prediction with Optimized Agricultural Resources** - This paper explores a system that uses AI to optimize irrigation and fertigation schedules based on short-term weather forecasts and soil conditions, demonstrating practical applications of AI in real-time weather prediction and agricultural resource management.
- **Understanding the Potential Applications of Artificial Intelligence in Agriculture** - This article provides insights into various AI applications in agriculture, including weather prediction, which helps in monitoring crops and optimizing agricultural practices.
- **An Artificial Intelligence-based Crop Recommendation System using Machine Learning** - Focuses on a crop recommendation system that incorporates AI for better crop management based on environmental factors.
- **Artificial Intelligence Models for Prediction of Monthly Rainfall** - Discusses AI models for rainfall prediction, which is directly relevant to developing accurate precipitation forecasts for farmers.
- **Implementation of Artificial Intelligence in Agriculture for Enhanced Crop Production** - Examines how AI technologies have improved crop production, real-time monitoring, and overall agricultural efficiency.
- **An Intelligent Agriculture Management System for Rainfall Prediction** - Highlights an AI-driven model using CNN and LSTM layers for predicting rainfall, offering insights into advanced AI techniques for accurate weather forecasting.