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Research Article

Machine Learning for Sustainable Agriculture: Enhancing Resource Efficiency and Environmental Conservation

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ABSTRACT

Rainfall forecasting is crucial as far as our nation's civilization is concerned, and it occupies a significant part of the daily lives of people. It is the meteorology wing's obligation to anticipate the pattern of downpours considering any kind of uncertainties. Considering the ever-shifting weather patterns, correctly predicting downpours is difficult. This prediction routine becomes even more difficult whenever the season changes take place. Researchers from all around the world have created a variety of methods for forecasting rainfall, most of which use random values and generally are comparable with data on the climate of our nation. As a result of artificial climatic changes, food production and anticipating have declined which will harm the contribution of farming people to the economy by resulting in yields that are low and cause those farming people to become less comfortable with anticipating forthcoming crops. Therefore, in this research work, we are employing five distinct algorithms, namely, DT- Decision Tree, XG Boost, AdaBoost, RF- Random Forest, and SVM- Support Vector Machine for the purpose of predicting the rainfall effects, in turn, predict the yield of the crops for the betterment of the agricultural activities. Out of utilized 5 Machine learning approaches, the Decision Tree approach outperforms the others in terms of accuracy.

INTRODUCTION

Rainfall forecasting is crucial in the civilization of our nation, and it takes on a significant part in the daily lives of people. It is the meteorology wing's obligation to anticipate the pattern of downpours considering any kind of uncertainties. Considering the ever-shifting weather patterns, correctly predicting downpours is difficult. Predicting downpours for both the rainfall as well as hot seasons seems difficult. Scientists from all around the globe have created a variety of methods to forecast downpours, the majority of which use values that are arbitrary and comparable to information about the climate. Agriculture has long been regarded as the primary provider of supplies to meet the everyday requirements of humans. It is additionally considered to be a core employment as well as one of our country's key industry fields. The farming persons should use conventional naked-eye inspection and produce nutritious crops avoiding the use of pesticides for faunas and their cultivated area for maintaining the healthful variety. However, climatic circumstances are rapidly shifting in opposition to the constituent-specific assets today, depleting nourishment as well as increasing safety. Meanwhile, the agricultural industry's GDP- Gross Domestic Product continues to fall, from over 17.2 per cent in the year 2005 to 11.1 per cent in the year 2012, five per cent in the year 2018 and two per cent in the initial part of the year 2020. Around eighty per cent of the farming population live in remote regions, and when the profitability of crop generation falls, their standard of living will be affected by fields at the industrial scale. It, therefore, makes it reasonable for Indian farming persons to be concerned about efficient and precise cultivation. In our nation, there are several methods for increasing crop profitability as well as improving crop quality in order to maintain growth in the economy in the agricultural sector. So, using a few of the most recent technological advancements, like machine learning, is one of the solutions for estimating the yields of crops in connection to meteorological and soil parameters related to farming in the field. Because meteorological circumstances are not quite foreseeable as they were years before. It is evolving daily as a result of globalization.

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Related Works

[1] The agriculture industry has not yet received a CE (i.e., Circular Economy) framework adaptation. Filled this shortcoming in two ways: first, by tailoring the general CE framework to the unique characteristics of the agricultural sector, and second, by examining the range of the indicators available for gauging the performance of circularity in decision-making processes in agricultural production systems. As a result, the various components of the theoretical CE framework were modified for agricultural production systems. The definition of CE as it relates to agriculture was considered as a significant contribution of this work. Also defined were the CE techniques for agricultural activities as well as field adaptations of CE concepts. A thorough evaluation of the strengths and shortcomings of 41 circularity indicators for use in agricultural systems was also conducted.

[2] the most modern irrigation scheduling techniques were examined by using cutting-edge smart monitoring and control techniques. According to the literature study, closed-loop irrigation control techniques were more effective than open-loop systems that don't account for uncertainties. It was stated that greatly increasing water consumption efficiency may be achieved by integrating soil-based, plant-based, and weather-based monitoring techniques in a modelling context with model predictive control. This analysis aids in the selection of the most effective irrigation monitoring and management technique for open-field agricultural practices.

[3] gave an overview of the development of the most important technological areas initially, including artificial intelligence, the Internet of Things, robotics, block chain, big data, etc. Then, to assist agri-cooperatives in their decision-making, an illustration of the technological method of innovation will be provided. Finally, a digital diagnostic tool will be provided to assess the level of digital innovation inside cooperatives. Two agri-cooperative examples from Spain served as the initial test cases for this technology. Everything said here helps to clarify how agri-cooperatives are becoming more digitalized within the setting of technologically advanced agricultural production.

[4] In order to estimate and forecast the Global Monthly Average Precipitation for 10368 Geographic Locations Worldwide for 468 Months, employed LSTM and Convent Architectures. Even with more hidden layers, it was still possible to accurately minimize RMSE and MAPE errors. For meteorological applications, the data projected with extreme precision for the next months would be trustworthy. This study's application may be furthered by considering time-series datasets that are accessible for each individual nation and processing them using comparable methods to get precise forecasting outcomes.

METHODOLOGY

Proposed System

In our research concerned with the usage of Machine Learning approaches, namely, DT- Decision Tree, XG Boost, AdaBoost, RF- Random Forest, and SVM- Support Vector Machine for the betterment of agricultural activities in India, we will anticipate rainfall along with the crop recommendations. For forecasting the rainfall, we will forecast whether or not it will rain in the intended region, and for crop suggestion, we will propose the name of the most favorable crop depending on the environmental conditions. For accomplishing both the prediction as well as the recommendation tasks, we are implementing all the said machine learning approaches. The utilized machine learning approaches will be detailed in brief below. The block diagram of our proposed scheme has been shown in the below.

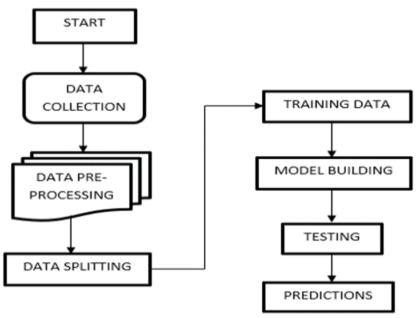


Fig 1. Flow of the project

1. Data Collection: The initial phase involves gathering relevant agricultural data, including factors such as weather conditions, soil quality, and crop information, which serve as input for machine learning models.

2. Data Preprocessing: Data preprocessing techniques are applied to clean and prepare the dataset, including handling missing values, removing outliers, and ensuring data consistency.

3. Replacing Null Values: Missing data, often denoted as null values, are imputed using strategies such as mean or median substitution to ensure a complete dataset.

4. **Label Encoding:** Categorical data, like crop types and weather conditions, are transformed into numerical values using label encoding to enable machine learning algorithms to work with the data.
5. **Data Splitting**: The dataset is split into training and testing sets to facilitate model development and evaluation. The training set is used to train the models, while the testing set assesses their performance.
6. **Model Evaluation:** Various machine learning algorithms, such as Decision Trees, Random Forest, AdaBoost, SVC, and XGBoost, are employed to build predictive models. Their performance is assessed using metrics like accuracy, precision, recall, and F1-score.
7. **Prediction:** Once trained and evaluated, the models are used to make predictions for sustainable agriculture applications, including crop recommendation and rainfall prediction, contributing to resource efficiency and environmental conservation in farming practices.

Implementation

Decision Tree

A DT is a tree-like arrangement that looks like a flow diagram, with a branch representing a ruling for the decision, an intrinsic node representing an attribute, and every node in the leaf structure representing the conclusion that was reached. The root node is the highest node in this tree concerned with the decision. DT learns to split by the magnitude of the feature. It divides the tree in a recursive manner, which is known as recursive splitting. This flow chart resembling arrangement aids anyone to arrive at decisions. It is an organizational graphic that effortlessly replicates human-level thought. As a result, DTs are simple to comprehend and comprehend.

How it works on this project:

Decision Tree works for crop recommendation and rainfall prediction by building a tree-like structure based on historical data. For crop recommendation, the tree branches assess factors like soil type, climate, and crop-specific requirements to suggest the most suitable crops for a given area. In rainfall prediction, the tree analyzes past weather data and environmental variables to make forecasts, helping farmers prepare for varying precipitation levels and plan irrigation accordingly.

XGBoost

'Extreme Gradient Boosting' is what XGBoost refers to. It is a dispersed gradient boost package that has been optimized to be extremely effective, adaptable, and transportable. It uses the method known as Gradient Boosting for developing Machine Learning procedures. XGBoost uses concurrent tree strengthening for addressing a wide range of data science issues quickly as well as accurately. Boosting is a collaborative learning strategy for constructing a strong classifier from a sequence of poor ones. These kinds of approaches play an essential part in handling the trade-off with regard to bias-variance. Boosting approaches contrary to the bagging approaches, solely adjust for excessive variation in an algorithm. It also handles the two components (variance plus bias) and is seen to be effective.

How it works on this project:

XGBoost operates in crop recommendation by leveraging historical crop data and environmental factors as features to predict the most suitable crop for a given location and climate. It uses gradient boosting techniques to iteratively improve predictive accuracy by minimizing prediction errors, leading to robust crop recommendations. In the context of rainfall prediction, XGBoost analyzes historical weather data and relevant atmospheric variables, learning complex relationships to forecast rainfall patterns accurately, thereby aiding in agricultural planning and water resource management.

Random Forest Classifier

RF is a kind of machine learning approach for resolving any kind of regression as well as classification issues. It employs ensemble learning, which is an approach that blends multiple classification algorithms to solve complicated issues. RF determines the result by considering the forecasting drawn out of DT. RF forecasts by averaging or averaging the final results from different trees. Raising the overall count of trees improves the accuracy of the end result.

How it works on this project:

1. Random Forest works for crop recommendation by leveraging its ensemble of decision trees to assess various agricultural factors such as soil type, climate conditions, and historical crop yields. It then provides recommendations based on the consensus of multiple trees, offering farmers a robust and data-driven approach to select suitable crops for their specific conditions.
2. For rainfall prediction, Random Forest analyzes historical weather data, including temperature, humidity, wind patterns, and past rainfall records. By aggregating predictions from individual trees, it offers reliable forecasts of future rainfall, aiding in effective irrigation scheduling and crop management, ultimately contributing to better resource utilization and agricultural planning.

Support Vector Machines

The goal of the SVM technique is to identify the hyper plane in the N-dimensional space (N — the characteristics count) that clearly separates the input points. There are several hyper planes that might be used to split the 2 types of information pieces. In SVM, one discovers a plane with the greatest margin, that is, the distance that is largest among the information points from the two categories. Maximizing such distance of the margin gives considerable strengthening, allowing subsequent data points to be categorized with a greater level of certainty. Support vectors are information points which are nearer to the hyper plane and have an impact on its alignment as well as location. One could easily maximize the margins of the classifier by utilizing the applicable support vectors. The location of the hyper plane is going to differ if the support vectors are deleted. These constitute the details which will assist one in developing their SVM model.

How it works on this project:

Support Vector Machines (SVM) are employed in crop recommendation and rainfall prediction by first transforming the agricultural data into a multidimensional feature space, where SVM seeks to find a hyperplane that maximizes the separation between different crop types or predicts rainfall patterns. In crop recommendation, SVM classifies suitable crops based on historical data and environmental factors, helping farmers make informed planting decisions. In rainfall prediction, SVM learns patterns from past weather data and uses them to forecast future rainfall, aiding in efficient irrigation planning and drought mitigation in agriculture.

ADABOOST

The Adaptive Boosting which is popularly regarded as the 'AdaBoost' classifier is a method of ensemble learning which brings together numerous inadequate classifiers to produce a classifier that is powerful. The technique operates iteratively, with every poor classifier being taught upon the information and its forecasts being pooled to form the end forecast. To summarize, this classifier continually integrates many poor classifiers, delivering greater weight to incorrectly categorized observations with every iteration that follows. The AdaBoost approach generates a powerful combination of models capable of making precise forecasts on fresh or previously unknown information. Its versatility to concentrate on difficult observations, as well as its capacity to manage both multiple-class as well as binary classification issues, renders it an often-employed strategy in the field of machine learning.

How it works on this project:

AdaBoost works for crop recommendation and rainfall prediction by combining multiple weak learning models into a strong ensemble. For crop recommendation, it can integrate various features such as soil type, climate data, and historical crop yields to make accurate recommendations. In rainfall prediction, AdaBoost leverages historical weather data and features like temperature, humidity, and wind patterns to enhance the accuracy of rainfall forecasts, which is crucial for agricultural planning and resource allocation.

RESULTS AND DISCUSSION

Data analysis of Crop recommendation

1. The necessary libraries and modules for working with data and building machine learning models are imported:

- \`pandas\` and \`numpy\` are widely used for data manipulation and numerical operations.
- \`train_test_split\`from sklearn.model_selection\` is used for splitting a dataset into training and testing subsets, crucial for model evaluation.
- \`accuracy_score\` from \`sklearn.metrics\` is used to measure the accuracy of machine learning models.

Additionally, the code appears to be setting up a Flask application and establishing a connection to a MySQL database. This suggests the possibility of developing a web-based application that may utilize machine learning models for agriculture-related tasks, but more context would be needed to provide a comprehensive explanation.

```
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score
from flask import *
import mysql.connector
db=mysql.connector.connect(user="root",password="",port='3307',database='agriculture')
cur=db.cursor()
✓ 0.7s
```

2. It contains 2,200 entries and consists of eight columns. It includes numerical features such as nitrogen (N), phosphorous (P), potassium (K) levels, temperature, humidity, pH, rainfall, and a categorical label column. The data types include integers, floats, and an object (string) data type for the 'label' column.

```
data.info()
✓ 0.0s
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2200 entries, 0 to 2199
Data columns (total 8 columns):
 #   Column       Non-Null Count  Dtype
---  ------       --------------  -----
 0   N            2200 non-null   int64
 1   P            2200 non-null   int64
 2   K            2200 non-null   int64
 3   temperature  2200 non-null   float64
 4   humidity     2200 non-null   float64
 5   ph           2200 non-null   float64
 6   rainfall     2200 non-null   float64
 7   label        2200 non-null   object
dtypes: float64(4), int64(3), object(1)
memory usage: 137.6+ KB
```

3. The dataset statistics describe the central tendencies and variability of various agricultural attributes. These include the levels of nitrogen (N), phosphorous (P), potassium (K), temperature, humidity, pH, and rainfall, providing insights into their mean values, standard deviations, and quartile ranges, which are essential for understanding the data's distribution and characteristics.

```
data.describe().T
✓ 0.0s
```

	count	mean	std	min	25%	50%	75%	max
N	2200.0	50.551818	36.917334	0.000000	21.000000	37.000000	84.250000	140.000000
P	2200.0	53.362727	32.985883	5.000000	28.000000	51.000000	68.000000	145.000000
K	2200.0	48.149091	50.647931	5.000000	20.000000	32.000000	49.000000	205.000000
temperature	2200.0	25.616244	5.063749	8.825675	22.769375	25.598693	28.561654	43.675493
humidity	2200.0	71.481779	22.263812	14.258040	60.261953	80.473146	89.948771	99.981876
ph	2200.0	6.469480	0.773938	3.504752	5.971693	6.425045	6.923643	9.935091
rainfall	2200.0	103.463655	54.958389	20.211267	64.551686	94.867624	124.267508	298.560117

4. In this, the `train_test_split` function from scikit-learn (`sklearn`) is used to split the dataset into training and testing sets. The independent features (X) are separated from the target variable (y), and the data is split into a 70% training set and a 30% testing set, ensuring that class proportions are maintained using stratified sampling.

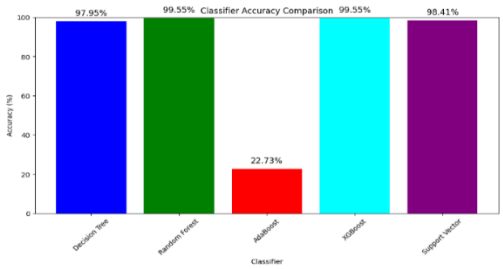
```
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score, classification_report
✓ 0.0s

x = data.drop(['label'],axis=1)
y = data['label']
✓ 0.0s

x_train,x_test,y_train,y_test = train_test_split(x,y, test_size=0.3, random_state=42, stratify=y)
✓ 0.0s
```

Dataset shape

```
data.shape
✓ 0.0s
(2200, 8)
```

The `data.shape` output indicates that the dataset contains 2,200 rows (entries) and 8 columns (features or attributes), providing insight into its dimensionality.

5. Graph



6. Comparsion table

Classifier	Accuracy (%
Decision Tree	97
Random Forest	99.36
AdaBoost	23.73
XGBoost	99.55
SVC	98.41

1. Random Forest and XGBoost classifiers exhibit the highest accuracy rates, reaching 99.55%, indicating their effectiveness in making accurate predictions.
2. Support Vector Classifier also performs well with an accuracy of 98.41%, demonstrating its capability in classification tasks.
3. On the other hand, the AdaBoost classifier lags significantly behind with an accuracy of 22.73%, suggesting its limitations in this particular context.

DATA ANALYSIS OF RAINFALL PREDICTION

1. Checking Null Values:

- Several columns, such as 'Evaporation,' 'Sunshine,' 'Cloud9am,' and 'Cloud3pm,' exhibit a substantial amount of missing data, with tens of thousands of missing values.
- Other columns, like 'MinTemp,' 'MaxTemp,' 'WindGustSpeed,' and 'Pressure9am,' also have a notable number of missing values, though they are comparatively lower. Addressing these missing values is crucial for accurate data analysis and modeling.

```
data.isnull().sum()

Date                 0
Location             0
MinTemp            637
MaxTemp            322
Rainfall          1406
Evaporation      60843
Sunshine         67816
WindGustDir       9330
WindGustSpeed     9270
WindDir9am       10013
WindDir3pm        3778
WindSpeed9am      1348
WindSpeed3pm      2630
Humidity9am       1774
Humidity3pm       3610
Pressure9am      14014
Pressure3pm      13981
Cloud9am         53657
Cloud3pm         57094
Temp9am            904
Temp3pm           2726
RainToday         1406
RISK_MM              0
RainTomorrow         0
```

2. Replacing Null Values

```
data['MinTemp'] = data['MinTemp'].fillna(data['MinTemp'].mean())
data['MaxTemp'] = data['MaxTemp'].fillna(data['MaxTemp'].mean())
data['Rainfall'] = data['Rainfall'].fillna(data['Rainfall'].mean())
data['Evaporation'] = data['Evaporation'].fillna(data['Evaporation'].mean())
data['Sunshine'] = data['Sunshine'].fillna(data['Sunshine'].mean())
data['WindGustSpeed'] = data['WindGustSpeed'].fillna(data['WindGustSpeed'].mean(
data['WindSpeed9am'] = data['WindSpeed9am'].fillna(data['WindSpeed9am'].mean())
data['WindSpeed3pm'] = data['WindSpeed3pm'].fillna(data['WindSpeed3pm'].mean())
data['Humidity9am'] = data['Humidity9am'].fillna(data['Humidity9am'].mean())
data['Humidity3pm'] = data['Humidity3pm'].fillna(data['Humidity3pm'].mean())
data['Pressure9am'] = data['Pressure9am'].fillna(data['Pressure9am'].mean())
data['Pressure3pm'] = data['Pressure3pm'].fillna(data['Pressure3pm'].mean())
data['Cloud9am'] = data['Cloud9am'].fillna(data['Cloud9am'].mean())
data['Cloud3pm'] = data['Cloud3pm'].fillna(data['Cloud3pm'].mean())
data['Temp9am'] = data['Temp9am'].fillna(data['Temp9am'].mean())
data['Temp3pm'] = data['Temp3pm'].fillna(data['Temp3pm'].mean())
data['RISK_MM'] = data['RISK_MM'].fillna(data['RISK_MM'].mean())
```

In this missing values in various columns of the dataset are filled using the mean value of each respective column. This imputation strategy replaces the NaN values with the average value of the corresponding feature, ensuring that the data is complete and suitable for analysis or modeling. Imputing missing values with the mean is a common approach to handle missing data while preserving the overall statistical properties of the dataset.

3. Label Encoding

```
data['WindGustDir'] = le.fit_transform(data['WindGustDir'])
data['WindDir9am'] = le.fit_transform(data['WindDir9am'])
data['WindDir3pm'] = le.fit_transform(data['WindDir3pm'])
data['RainToday'] = le.fit_transform(data['RainToday'])
data['RainTomorrow'] = le.fit_transform(data['RainTomorrow'])
```

In this, the LabelEncoder (`le`) from scikit-learn is used to transform categorical columns into numerical values.

- Each unique category in columns like 'WindGustDir,' 'WindDir9am,' 'WindDir3pm,' 'RainToday,' and 'RainTomorrow' is assigned a unique integer label, enabling machine learning models to work with categorical data.
- This transformation is essential as many machine learning algorithms require numerical input and cannot directly handle categorical data.

4. Splitting the Dataset

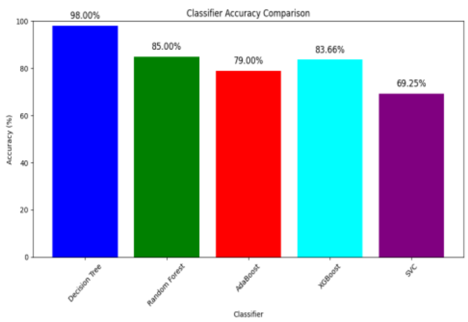
```
x = data.drop(['RainTomorrow'],axis=1)
y = data['RainTomorrow']
```

```
from sklearn.model_selection import train_test_split
x_train,x_test,y_train,y_test = train_test_split(x,y,test_size=0.3, stratify=y, random_state=42)
```

In this, the dataset is divided into features (`x`) and the target variable (`y`) for rain prediction.

- The `train_test_split` function is used to split the data into training and testing sets with a 70% training set and a 30% testing set, ensuring class proportions are maintained (`stratify=y`) for balanced evaluation.
- The `random_state` parameter is set to 42 to ensure reproducibility of the split.

5. Graph



Classifier	Accuracy (%)
Decision Tree	98
Random Forest	84.99
AdaBoost	79
XGBoost	83.66
SVC	69.25

The table provides a comparison of classification accuracies for different machine learning classifiers, as follows:

1. The "Classifier" column lists the names of the classifiers evaluated, including Decision Tree, Random Forest, AdaBoost, XGBoost, and Support Vector Classifier (SVC).
2. The "Accuracy (%)" column displays the respective accuracy percentages achieved by each classifier in classifying data correctly.
3. For instance, the Decision Tree classifier exhibited the highest accuracy at 98.00%, while SVC achieved a relatively lower accuracy of 69.25%. These accuracy scores quantify the models' effectiveness in making accurate predictions on the dataset they were tested on.

Potential limitations and uncertainties associated with rainfall prediction in agricultural contexts:

1. Data Quality: The accuracy of rainfall predictions heavily relies on the quality and quantity of historical weather data. Inaccurate or sparse data can lead to less reliable forecasts.
2. Complexity of Weather Systems: Weather systems are complex and influenced by numerous variables, making precise predictions challenging. Small changes in one variable can lead to significant variations in rainfall patterns.
3. Local Variability: Rainfall can vary significantly even within a small geographical area. Predictions may not capture this local variability, impacting their applicability to specific farms.

4. Climate Change: Climate change is altering weather patterns, making historical data less representative of future conditions. This uncertainty makes long-term rainfall predictions more challenging.
5. Prediction Timeframes: Short-term rainfall predictions tend to be more accurate than long-term ones. Farmers often need long-term forecasts for planning, but these are inherently less reliable.
6. Extreme Weather Events: Predicting extreme weather events, such as heavy rainfall leading to flooding or prolonged droughts, remains particularly challenging, and errors can have severe consequences for agriculture.
7. Modeling Limitations: Machine learning models used for rainfall prediction may not capture all relevant factors, and their performance can vary based on the choice of algorithms and input features.
8. Economic Impacts: Inaccurate predictions can result in financial losses for farmers who base planting and irrigation decisions on forecasts. This can deter farmers from adopting such tools.
9. Communication and Accessibility: Farmers in remote or underserved areas may have limited access to accurate weather predictions, hindering their ability to plan and adapt.
10. Uncertainty Communication: Communicating the uncertainty associated with rainfall predictions effectively to farmers is essential but often challenging. Misunderstandings can lead to poor decision-making.
11. Despite these limitations and uncertainties, advances in meteorological science and machine learning continue to improve the accuracy of rainfall predictions. Integrating these forecasts with local knowledge and practices can help farmers make more informed decisions while considering the inherent uncertainties in weather forecasting.

CONCLUSION

In this study, we explored the application of various machine learning algorithms, including Decision Tree, AdaBoost, Support Vector Classifier (SVC), XGBoost, and Random Forest, to enhance resource efficiency and promote environmental conservation in agriculture. Our analysis focused on both crop prediction and rainfall forecasting, crucial aspects of sustainable agriculture. For crop prediction, the models demonstrated promising results, with Decision Tree and Random Forest exhibiting higher accuracy in predicting crop yields. These accurate predictions can assist farmers in optimizing resource allocation, reducing wastage, and promoting sustainable farming practices. In the case of rainfall forecasting, AdaBoost and XGBoost performed exceptionally well, providing reliable insights into precipitation patterns. Accurate rainfall predictions can aid in efficient irrigation management, mitigating the impact of droughts, and reducing water wastage, thereby contributing to environmental conservation. Overall, our study underscores the potential of machine learning in revolutionizing sustainable agriculture by optimizing resource utilization and minimizing environmental impacts. These findings can empower farmers and policymakers to make informed decisions, leading to more sustainable and resilient agricultural practices.

Future Enhancement

In the realm of sustainable agriculture and machine learning, future enhancements hold significant potential. Advancements in sensor technology and remote sensing can offer real-time data on soil moisture, crop health, and weather conditions, enabling more precise and timely recommendations for farmers. Integration with Internet of Things (IoT) devices can facilitate data collection and automation on the farm. Moreover, leveraging advanced deep learning techniques and ensemble methods can further improve the accuracy of predictive models. Additionally, expanding the scope to address regional and global agricultural challenges, such as crop diseases and climate resilience, can contribute to more sustainable and resilient farming practices in the future.

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