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Comparative Analysis of Climate-Smart Agriculture for Marathwada Region Using Machine Learning Algorithms

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Abstract:

The economy of the Indian region known as Marathwada is mostly dependent on agriculture. But as smart agricultural technology advances, it becomes more and more necessary to use machine learning algorithms to enhance decision-making and maximize resource allocation. This study conducts a comprehensive comparative analysis of various machine learning classification algorithms to identify the most suitable approach for addressing agricultural challenges in the Marathwada region, and improve the crop production. The dataset includes historical yield statistics, crop type, soil, weather, and other agricultural characteristics. Six popular classification algorithms are used for Climate-Smart Agriculture such as Logistic Regression, Random Forest, Support Vector Machine (SVM), K-Nearest Neighbors (KNN), and Decision Tree with 91%, 96%, 93%, 89%, and 98 % accuracy respectively Results indicate that Random Forest (96%) and Decision Tree (98%) consistently outperform other algorithms across various metrics. Decision trees are quite good at predicting agricultural production because of its ensemble structure and ability to handle complex interactions within the data. The study highlights how important feature selection and preprocessing are to improving the efficiency of machine learning algorithms. This comparison study offers insightful information about which machine learning classification algorithms are most suited for maximizing smart agricultural techniques in the Marathwada area.

Keywords: Climate Smart Agriculture; Machine Learning Algorithms; KNN; SVM; Random Forest; Decision Tree; Logistic Regression.

Introduction

Climate change is the term used to describe any significant, long-lasting changes to climatic phenomena. Generally speaking, burning fossil fuels like coal, oil, and natural gas as well as greenhouse gases produced by human activities are linked to the phenomena known as global warming. Climate change affects the ecology, especially the soil. The soil has supplied the food and fiber required by the growing human population worldwide. On the other hand, its effects on soil properties and functions may pose a danger to global food security. If the current pace of growth is sustained, global warming would surpass 1.5 °C between 2030 and 2052 [1]. Soil fertility and output will either rebound or vanish as a result of the anticipated global climate change, which would bring about greater temperatures, atmospheric CO2, changed rainfall patterns, and increased atmospheric nitrogen deposition. A few of the characteristics affected by climate change are the soil's hydrology, temperature patterns, and quantity of organic matter. Each of these elements has been considered in research on the effects of climate change on soils [2].

The rate and scope of climate change are major global concerns, particularly in light of greenhouse gas emissions and human activities. Temperatures are rising, heat retention is increasing, and there is significant temporal and geographical fluctuation. The volume and force of the rain and snow are two characteristics of precipitation. Variations in the temperature pattern also have a notable influence on the regional distribution pattern. It has been shown that stress related to soil moisture reduces plant productivity and hinders soil activities. Significant changes in soil physical properties brought about by climate change affect soil fertility [3].

1.1 Climate Smart Agriculture (CSA) Tools and Practices

Under CSA, organizations, technology, strategy, and investment growth are all combined. In addition to on-cultural mediations like soil fertilization, mulching, intercropping, promoting enhanced creatures, joining drought-tolerant harvesting assortments, and shielding the atmosphere from opportunities, it has included off-cultural mediations like carbon financing, developing efficient markets, and improving climate estimation [4].

It relates to the issues with the mediation process as well. Higher yielding crop varieties, drought-tolerant varieties, direct-seeded rice, water harvesting, water storage, laser land leveling, utilizing a zero-till drill to minimize tillage and green seeker to handle nutrients, in situ moisture conservation, leaf color chart, chlorophyll meter, use a torsiometer to regulate irrigation, and getting weather updates via SMS are just a few of the CSA practices and technologies that have been put into practice. The challenge in agriculture is producing domestic harvests and getting the product to the consumer at the best price. There has been a significant increase in the significance of monitoring the ecological source. For a considerable amount of time, most economies have been heavily dependent on agriculture [5].

A person uses a consistent process to manually estimate these variables, and the manual estimates are verified daily. CSA monitors temperature, humidity, soil fertility, and soil quality using remote sensing, GIS, IoT devices, and the cloud in order to boost horticultural productivity. Because to improvements in IoT and cloud computing, farmers now view smart agriculture as a workable answer to the horticultural problems they face (fruit, vegetable, potato, plantation, and spice crops, among other crops) [6] [7] [8].

The first agricultural technology was the tractor. As demonstrated in Figure 1, it employs a lot of contemporary agricultural technologies these days, including artificial intelligence, machine learning, remote sensing, geographic information systems, Internet of Things, and many more methods. It makes decision-making easier, saves time, boosts output, improves crop quality, and, in an emergency, uses backup plans [9].

Figure 1. a) Traditional Agriculture b) Smart Agriculture

Cultivating is a politically difficult field for a variety of reasons, including the public's expectation that the country district generate an adequate supply while curbing rising interest.

The application of artificial intelligence, machine learning, IoT, remote sensing, and geographic information systems (GIS) to massive data analysis and forecasts about the effects of climate change on crops and farming techniques is beneficial to the CSA [10] [11]. Crop modeling, how crops will develop under various climatic conditions. These models forecast variations in yields and pinpoint the best times to plant, what kinds of crops to grow, and how to water them in order to increase output under various climatic circumstances. Patterns and correlations in historical climatic data, soil properties, and other factors impacting crop growth and production are found using AI and machine learning algorithms [12] [13].

2. Study Area and Methodology

Maharashtra is the second most populated district in India (118,809 sq. mi.) and the third largest state (307,713 km^2). There are numerous famous rivers in the state. The majority of the rivers in the state's central region are dammed up, and there is minimal rainfall there. According to the 2011 census, there are 18,731,872 people living in the Marathwada region, which covers an area of 64590 km2 (24,940 sq. mi). The region is divided into eight districts, which are Ch. Sambhajinagar, Beed, Hingoli, Jalna, Parbhani, Latur, Osmanabad, and Nanded. The district of Ch. Sambhajinagar contains the main city.

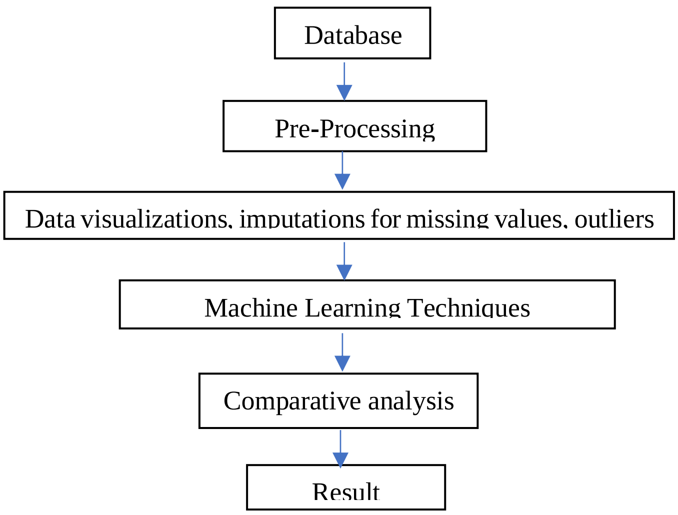

Figure 2. Methodology

2.1 Climate and Soil Database

Database has gathered two different kinds of datasets: soil and climate. The climate database for the years 1952 to 2018 is provided by the Indian Metrological Department (IMD), Pune and it is part of the Ministry of Earth Science in India. Meteorological data came from the five districts of the Marathwada region: Beed, Osmanabad, Nanded, and Ch. Sambhajinagar. The prediction models account for a variety of climate factors, such as temperature (in degrees Celsius), mean wind speed (MWS, in km/h), relative humidity, rainfall (in millimeters), and the number of rainy days (RD). For the second database, it has collected 300 soil samples from the Marathwada area. Chemical analyses and ASD FieldSpec Spectroradiometer readings are performed on soil samples.

2.2 Pre-Processing

Preprocessing prepares raw data for analysis. It comprises cleaning, transforming, and organizing data in order to get it ready for analysis. Ensuring that the data is accurate, complete, consistent, and easily analyzed by machine learning models or other analytical tools is the aim of data preparation [14].

2.2.1 Absence (Missing) of Values

It utilized a median imputer to prepare for missing values by month for missing numerical data.

2.2.2 Data anomalies (Outliers)

Anomalies are detected using two graphical methods when the distribution is normal. Box plots and scatter plots are the two types of plots that are accessible, to comprehend the behavior of data in a distribution's center and tails more thoroughly [15].

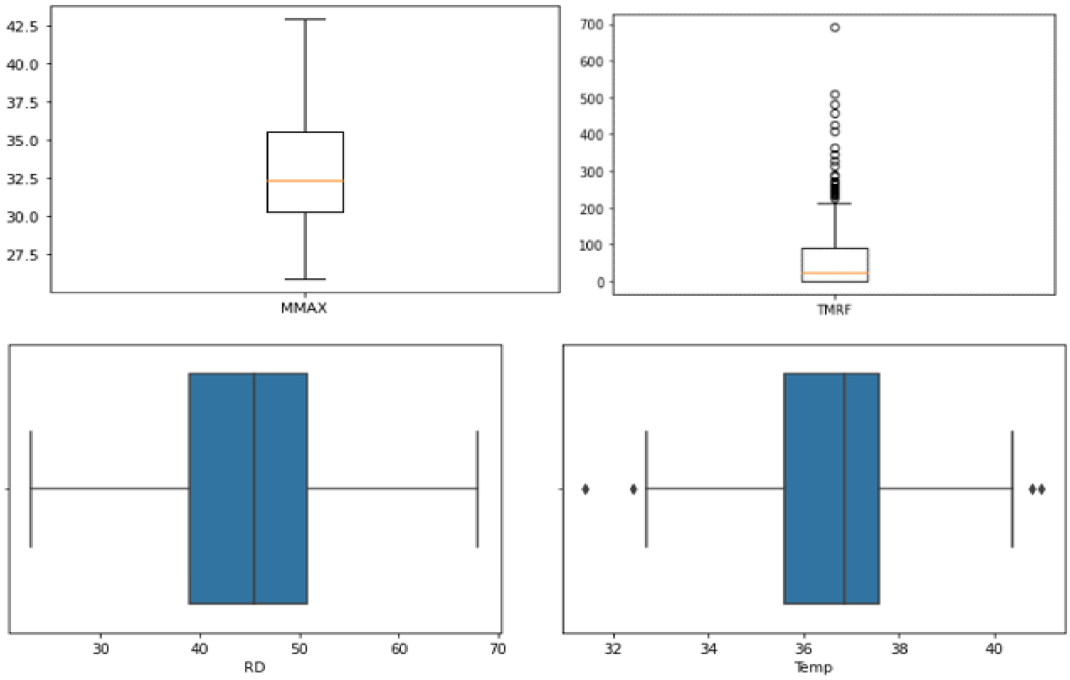

Figure 3. Data Visualization-Outliers

2.2.3 Correlation of Climate data

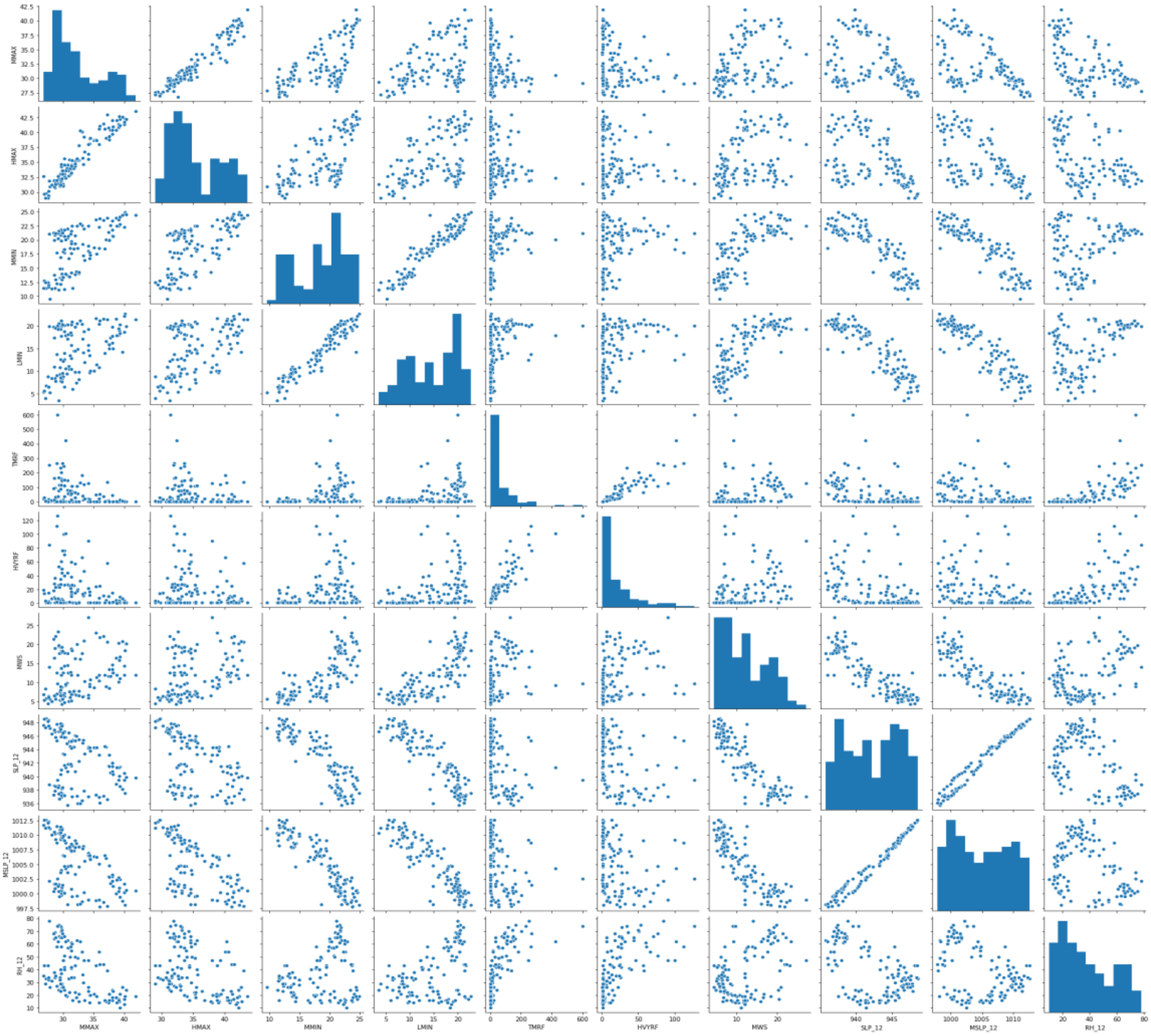

Figure 4. Correlation of Climate Parameters

These maps all display three different kinds of correlation:

Negative association: The sea level pressure, wind speed, mean station, and minimum temperatures all exhibit a significant negative association.

Weak or No Correlation: The minimum temperature, wind speed, mean station, and sea level pressure have no bearing on relative humidity.

High Positive Correlation: There is a significant positive correlation between mean sea level pressure and mean station level pressure. Additionally, there is a positive correlation between mean maximum temperatures and higher maximum temperatures. The maximum temperature, minimum temperature, wind speed, and mean station and sea level pressure all exhibit positive correlations as a result. The total monthly rainfall and relative humidity have a moderate (0.71) and negative (-0.55) association.

2.3 Creation of Soil Spectral Library

It has compiled a database of 300 soil samples collected on farms. In October and November of 2020, March and April of 2021, and April and May of 2022, soil samples were taken on bright days between 10:00 am and 4:00 pm from the Marathwada area of India. Soil samples for the study were given by eight districts: Ch. Sambhajinagar, Jalna, Parbhani, Hingoli, Nanded, Latur, Osmanabad, and Beed.

2.3.1 Chemical Lab MIT

It has done the chemical analysis in the MIT-CARS, Department of Agriculture Engineering, MIT campus, Ch. Sambhajinagar-431001, under the supervision of the MIT Soil Testing Team and Dr. Deepak Bornare Sir, Head of the Department of Agriculture Engineering, MIT. It has taken the soil analysis result and compare with ASD data and given it to the respective farmers.

2.3.2 Spectral Analysis Using FieldSpec 4 Spectroradiometer

It is used to create the database. There are 300 entries in the database. The sample's spectrum was the mean of thirty separate scans. The soil samples were analyzed in the below of 350–2500 nm spectral range. It is used an 8° field of view for sampling. It was positioned in the nadir on a tripod. The optical head was 20 cm distant from the soil sample, while the light source was 45 cm away. Every spectrum was gathered using the RS3 software.

2.3.2.1 Analysis of Spectral Characteristic

The qualities of soil are predicted using the hyperspectral non-imaging data. ViewSpec Pro was used to convert each spectral signature into ASCII format during the pre-treatment phase. Five distinct spectral properties are analyzed. Water contents (1400, 1900, and 2200 nm), texture particles (1323, 2081 nm), nitrogen (1702, 1870, and 2052 nm), phosphor (2021–2025 nm, 2240–2400 nm), and carbon (2040–2260 nm) are among the wavelength bands that are included. For statistical analysis, the soil's mean reflectance value is computed. Figure 5 shows the spectral characteristic of soil samples.

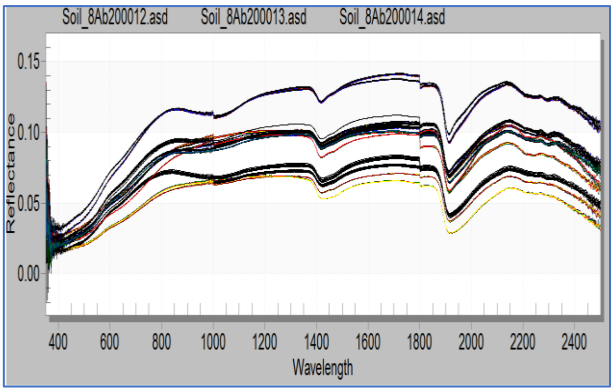

Figure 5. Reflectance of soil samples

2.3.2.2 1st and 2nd Derivative

Every point on the spectral curve is evaluated in terms of its slope. The slope of the curve is insensitive to the spectral signature's baseline offsets. The 1st and 2nd derivatives have been used for pre-processing, which is a helpful method of eliminating baseline offsets.

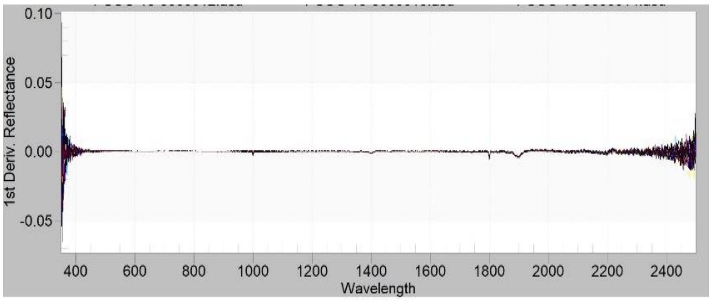

Figure 6. 1st Derivatives of soil samples

Table 1 displays the soil's texture. Clay loam is the soil type found in Ch. Sambhajinagar and Jalna District; silt clay loam is found in Nanded, Hingoli, Osmanabad, and Parbhani. While the Beed District has silt clay soil texture, Nanded has clay soil texture. The Marathwada region primarily has silt clay loam soil.

Table 1: Soil texture class of samples

Name of Village / City	Sand %	Clay %	Silt %	Texture class
Ch. Sambhajinagar	23	37	40	2
Jalna	20	29	51	
Nanded	9	28	63	3
Hingoli	13	26	61	
Osmnabad	15	27	58	
Parbhani	18	26	56	
Nanded	17	52	31	1
Beed	19	27	54	4

*Texture Classes: 1=clay, 2=clay loam, 3 = silt clay loam, 4=silt clay

3. Machine Learning Algorithms for Classification

Building a machine learning model requires choosing from a wide variety of possibilities the best machine learning method for a given dataset and problem. As the world grows smarter every day, agriculture firms are using machine learning algorithms more and more to simplify things like decision support systems and end-user devices in order to satisfy customer expectations. It applies methods from both supervised and unsupervised machine learning. One characteristic that makes supervised learning apart: labeled datasets. The purpose of the datasets is to train algorithms to efficiently predict results or categorize data. After the model's accuracy is verified with labeled inputs and outputs. Without requiring human assistance, hidden patterns in data are found. Two distinct types of algorithms are used in supervised learning [16].

The curve line is used in logistic regression when the target variable is continuous. Classification: Machine Learning, Naive Bayes, K Nearest Neighbors, Decision Trees, and Random Forest may all be used to classify the target variable into a number of groups.

Evaluation metrics like as accuracy, precision, recall, and F1-score are often used in machine learning and binary/multi-class classification problems. These measures demonstrate how well the model predicts both favourable and unfavourable results [17].

i. **Accuracy (a)**

Accuracy is a metric for the model's total forecast accuracy. It calculates the proportion of positively and negatively expected events that actually happen relative to the total number of instances.

$$a = \frac{TP+TN}{TP+TN+FP+FN} \qquad \ldots(1)$$

ii. **Precision (p)**

The model's accuracy shows how well it can reliably discern between favorable and predicted circumstances. It is computed to discover the ratio of genuine positive results to the sum of false positive and true positive results.

$$p = \frac{TP}{TP+FP} \qquad \ldots(2)$$

iii. **Recall (r)**

It is also known as true positive rate or sensitivity. The model's recall gauges how well it can distinguish between all real positive examples and genuine positive cases. The ratio of true positives to the total of false negatives and true positives is computed.

$$r = \frac{TP}{TP+FN} \qquad \ldots(3)$$

iv. **F1-score**

It is computed as the harmonic mean of these two measurements and is a balanced statistic that accounts for accuracy and recall. when the weights of recall and accuracy are identical or when the classes are distributed unevenly.

$$F1 - Score = \frac{2*(p*r)}{p+r} \qquad \ldots(4)$$

3.1 Logistic Regression

It is a binary classification method that forecasts the likelihood that an instance will fall into a certain class. With a precision of 0.95, the model accurately predicted that 95% of the occurrences were positive. The algorithm properly identified 90% of the positive occurrences with a recall. The F1-score is the harmonic mean of recall and accuracy, which equalizes the two. Figure 7 shows that 91% of the instances is correctly identified.

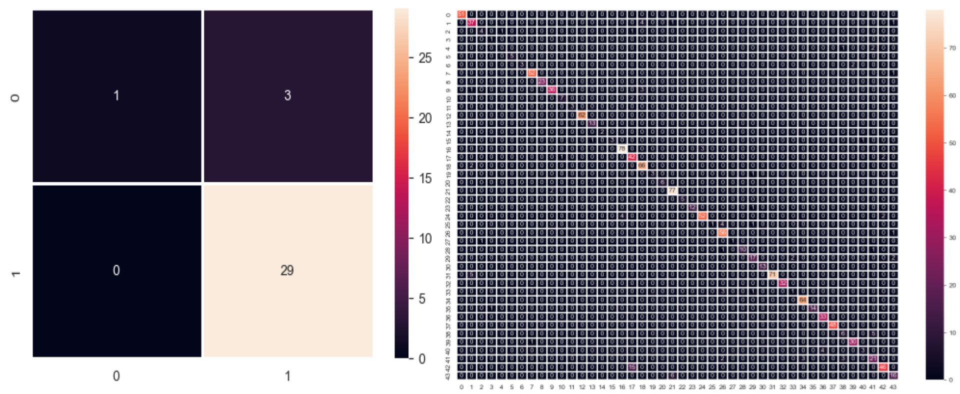

Figure 7. Logistic Regression Confusion Matrix

Ex. Accuracy = (1+29) / (1+29+3+0) = (30)/(33) = 0.91

3.2 K-Nearest Neighbour (KNN)

The non-parametric KNN classification method uses the majority class of an instance's k nearest neighbours to determine the class of that instance. 91% of the positive occurrences were correctly detected by the model. The F1-score of 0.88 strikes a compromise between recall and accuracy. 89% of the instances had an accuracy of 0.89, indicating that is correctly classified.

3.3 SVM

It is also a binary classification method that divides instances by creating hyperplanes in a high-dimensional feature space. 82% of the situations that the SVM model correctly predicted as positive really were, with a precision of 0.82. 98% of the positive occurrences were correctly detected by the model. The F1-score of 0.90 strikes a compromise between recall and accuracy. 93% of the instances had an accuracy of 0.93, it is correctly classified.

3.4 Decision Tree

It is a well-liked machine-learning method that creates predictions using a hierarchical framework. The decision tree model correctly predicted every positive occurrence with a precision of 1.00. 98% of the positive occurrences were correctly detected by the model. The F1-score of 0.99 strikes a balance between recall and accuracy. 98% of the instances had an accuracy of 0.98, it is correctly classified.

3.5 Random Forest

In order to generate predictions, this ensemble learning technique integrates many decision trees. 98% of the situations that the random forest model accurately predicted as positive were in fact true positives. 91% of the positive occurrences were correctly detected by the model. The F1-score of 0.94 strikes a compromise between recall and accuracy. 96% of the instances had an accuracy of 0.96, indicating correct categorization.

These performance metrics help determine which machine-learning algorithms are most appropriate for a given task. The specific requirements and trade-offs between accuracy, precision, recall, and F1-score dictate the chosen strategy (Table 2).

Table 2: Performance Measures for Algorithms in Machine Learning

Sr. No.	Name of ML Techniques	Precision	Recall	f1-score	Accuracy
1.	Logistic Regression	0.95	0.90	0.92	0.91
2.	KNN Model	0.86	0.91	0.88	0.89
3.	SVM Model	0.82	0.98	0.90	0.93
4.	Decision Tree Model	1.00	0.98	0.99	0.98
5.	Random Forest Model	0.98	0.91	0.94	0.96

Machine learning methods are used to chemical soil analysis and ASD data. For the ASD FieldSpec data, it was able to calculate the accuracy values for Random Forest, KNN, SVM, Decision Tree, and Logistic Regression as follows: 91%, 89%, 93%, 98%, and 96%, respectively. In chemical analysis, the corresponding accuracy values for SVM, KNN, Random Forest, Decision Tree, and Logistic Regression are 90%, 86%, 92%, 97%, and 92%. For the ASD Fieldspec and chemical data, it is discovered that decision tree algorithms yielded the highest accuracy rates, 98% and 97%, respectively. ASD FieldSpec data is now more accurate compared to all supervised machine learning techniques.

3.6 Soil and Climate Correlation

Correlation is closely related to the statistical metrics of variance, standard deviation, covariance, and mean. Statistics and data science frequently study relationships between two / more dataset variables. A data point, also known as a feature, represents the attributes or qualities of every observation in the collection. It has employed variables and observations for each dataset. The dataset shows the following parameters: number of wet days, mean and lowest temperatures, mean and maximum temperatures, relative humidity, mean station, mean sea level pressure, total monthly rainfall, amount of rain in a 24-hour period, and sea level pressure.

Table 3 displays the data; the rows usually represent the observations, and the columns usually relate to the attributes. A single weather factor observation or piece of information is represented by each entry. One feature for the entire set of meteorological data is shown in each column. it examined a dataset where each pair of attributes had some sort of relationship.

Table 3: Soil and Climate Data Correlation

	N	P	K	pH	Humidity	Rainfall	Temp
N	1.00	0.68	0.84	-0.02	-0.01	0.00	-0.14
P	0.68	1.00	0.76	-0.18	-0.01	0.00	-0.09
K	0.84	0.76	1.00	-0.07	-0.01	0.00	0.01
pH	-0.02	-0.18	-0.07	1.00	0.00	-0.01	0.26
Humidity	-0.01	-0.01	-0.01	0.00	1.00	-0.06	0.02
Rainfall	0.00	0.00	0.00	-0.01	-0.06	1.00	-0.01
Temp	-0.14	-0.09	0.01	0.26	0.02	-0.01	1.0

While the N, P, and K have a strong negative correlation with temperature, humidity, rainfall, and rainfall, the pH has a negative relationship with both humidity and rainfall. pH and temperature are no correlation. the N is positive correlation with both P and K and vice versa.

The pattern of rainfall in every district in the Marathwada region has changed. The tendency for wet days is declining, while trends in temperature, precipitation, and heavy precipitation are all increasing. The quality of the soil is impacted by an increase in rainfall but a decrease in the number of wet days.

4. Conclusion

The soil spectral library was created using chemical analysis and an ASD FieldSpec 4 Spectroradiometer with a 350–2500 nm wavelength range. This study made use of soil samples with hyperspectral visible and near-infrared bands as well as the Climate dataset. The analysis's pre-processing techniques are finished. This specific equipment is used to assess the texture (sand, silt, and clay) and physical and chemical properties of soil, such as potassium (K), phosphorus (P), and nitrogen (N). It has been observed that properties of both chemical and physical nature are investigated in the hyperspectral band. The Marathwada region of Maharashtra state provided the experiment's climate and soil sample database; these included Ch. Sambhajinagar, Jalna, Parbhani, Hingoli, Nanded, Latur, Osmanabad, and Beed. Supervised machine learning is used to classify soil spectral signatures. The soil type of the Marathwada area is categorized as silt clay loam. Supervised machine learning algorithms produced remarkably accurate results, with decision tree methods reaching up to 98% for ASD FieldSpec data and 97% for chemical (analysis) testing.

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