

CS19411-PYTHON PROGRAMMING FOR MACHINE LEARNING

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MINI PROJECT REPORT

SMART IRRIGATION SYSTEM USING MACHINE LEARNING

AIM:

This project focuses on developing a Smart Irrigation System leveraging machine learning techniques to optimize water usage in agriculture. By analysing environmental factors such as soil moisture, temperature, humidity, and rainfall predictions, the system ensures efficient water distribution. The model achieved X% accuracy in predicting irrigation requirements, showcasing its potential for sustainable agricultural practices.

SVM Model Implementation:

Step 1: Initiating the hyperparameters .

Step 2: Fitting the dataset to SVM Classifier.

Step 3: Implementing Gradient Descent algorithm for Optimization.

Step 4: Predict the label for a given input value.

PROGRAM CODE:

```
import numpy as np

import seaborn as sns

import pandas as pd

import matplotlib.pyplot as plt

# INITIATING THE HYPERPARAMETERS

class SVM:

    def __init__(self, learning_rate, no_of_iterations, lambda_parameter):

        self.learning_rate = learning_rate

        self.no_of_iterations = no_of_iterations

        self.lambda_parameter = lambda_parameter


# fitting the dataset to SVM Classifier

def fit(self, X, Y):

    # m --> number of Data points --> number of rows

    # n --> number of input features --> number of columns

    self.m, self.n = X.shape

    # initiating the weight value and bias value

    self.w = np.zeros(self.n)

    self.b = 0

    self.X = X

    self.Y = Y
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# implementing Gradient Descent algorithm for Optimization

for i in range(self.no_of_iterations): # Now within the fit method
    self.update_weights()

# function for updating the weight and bias value
def update_weights(self):
    # label encoding
    y_label = np.where(self.Y <= 0, -1, 1)

    # gradients ( dw, db)

    for index, x_i in enumerate(self.X): #Fixed: Corrected indentation for this line
        condition = y_label[index] * (np.dot(x_i, self.w) - self.b) >= 1

        if (condition == True):
            dw = 2 * self.lambda_parameter * self.w

            db = 0

        else:
            dw = 2 * self.lambda_parameter * self.w - np.dot(x_i, y_label[index])
            db = y_label[index]

        self.w = self.w - self.learning_rate * dw
        self.b = self.b - self.learning_rate * db

    # predict the label for a given input value
    def predict(self, X):
        output = np.dot(X, self.w) - self.b
        predicted_labels = np.sign(output)
        y_hat = np.where(predicted_labels <= -1, 0, 1)

        return y_hat

from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score

# LOADING THE DATA FROM CSV FILES TO PANDA DATAFRAME
crop_data = pd.read_csv('/content/projectdata2.csv')

#PRINT FIRST 5 ROWS OF THE DATAFRAME
crop_data.head()

#NUMBER OF ROW AND COLUMNS IN A DATASET
crop_data.shape

#GETTING STATISTICAL MEASURES OF THE DATASET
crop_data.describe()

#COUNT OF THE DATASET
if 'Days_to_Harvest' not in crop_data.columns:
    print(f"Available columns: {crop_data.columns.tolist()}")

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else:

print(crop_data['Days_to_Harvest'].value_counts())

features = crop_data.drop(columns='irrigation_frequency', axis=1)

target = crop_data['irrigation_frequency']

print(target)

# Import necessary libraries

import pandas as pd

from sklearn.preprocessing import StandardScaler

# Assuming 'features' is the DataFrame

# Select only numerical features for scaling

numerical_features = features.select_dtypes(include=['number']).columns

features_to_scale = features[numerical_features]

# Now fit the scaler on the numerical features only

scaler = StandardScaler()

scaler.fit(features_to_scale)

# Transform only the numerical features

standardized_data_numerical = scaler.transform(features_to_scale)

# 1. Create a new DataFrame with standardized numerical features

standardized_data = pd.DataFrame(standardized_data_numerical, columns=numerical_features, index=features.index)

# 2. Concatenate the standardized numerical features with the original non-numerical features

standardized_data = pd.concat([standardized_data, features.drop(columns=numerical_features)], axis=1)

print(standardized_data)

features = standardized_data

target = crop_data['irrigation_frequency']

print(features)

print(target)

X_train, X_test, Y_train, Y_test = train_test_split(features, target, test_size=0.2, random_state = 2)

print(features.shape, X_train.shape, X_test.shape)

from sklearn.svm import SVC

classifier = SVC(kernel='linear', C=1/0.01)

!pip install -q pandas scikit-learn

import pandas as pd

from sklearn.preprocessing import OneHotEncoder

from sklearn.compose import ColumnTransformer

from sklearn.model_selection import train_test_split

from sklearn.svm import SVC

from sklearn.impute import SimpleImputer

categorical_features = ['crop']

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numerical_features = features.drop(columns=categorical_features).columns

# Create a ColumnTransformer to apply OneHotEncoder to categorical features
# and SimpleImputer to handle NaN values

preprocessor = ColumnTransformer(
transformers=[

('num', SimpleImputer(strategy='mean'), numerical_features), # Impute numerical features
('cat', OneHotEncoder(sparse_output=False, handle_unknown='ignore'), categorical_features),

])

# Fit and transform the data

features_encoded = preprocessor.fit_transform(features)

# Split the encoded data into training and testing sets
X_train, X_test, Y_train, Y_test = train_test_split(features_encoded, target, test_size=0.2, random_state=2)

# Create and train the SVC classifier

classifier = SVC(kernel='linear', C=1/0.01)

classifier.fit(X_train, Y_train)

print(features_encoded.shape, X_train.shape, X_test.shape)

# accuracy on training data

X_train_prediction = classifier.predict(X_train)

training_data_accuracy = accuracy_score(Y_train, X_train_prediction)

print('Accuracy score on training data = ', training_data_accuracy)

# accuracy on training data

X_test_prediction = classifier.predict(X_test)

test_data_accuracy = accuracy_score(Y_test, X_test_prediction)

print('Accuracy score on test data = ', test_data_accuracy)

# BUILD A PREDICTIVE SYSTEM

# Input sequence from the user

input_sequence = input("Enter the crop: ")

# Create a DataFrame with all expected columns

input_data = pd.DataFrame({

'crop': [input_sequence],

'temperature': [0],

'humidity': [0],

'ph': [0],

'rainfall': [0],

'sunlight_exposure': [0],

'soil_moisture': [0],

'soil_type': [0],

'wind_speed': [0],

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'water_source_type':[0],
'frost_risk':[0],
'water_usage_efficiency':[0]
})

# Preprocess the input data using the same preprocessor used for training
try:

input_encoded = preprocessor.transform(input_data)

# Make prediction using the trained classifier
prediction = classifier.predict(input_encoded)

# Print the predicted irrigation
print("Predicted irrigation:", prediction[0])

except ValueError as e:

print(f"Error during prediction: {e}")

print("Please ensure the input sequence and other features are in the correct format.")


# Distribution of the target variable
plt.figure(figsize=(14, 12))

sns.countplot(x=target)

plt.title('Distribution of Irrigation Prediction')

plt.show()

#Comparison of training and testing accuracy
accuracy_scores = {'Training': training_data_accuracy, 'Testing': test_data_accuracy}

plt.figure(figsize=(14, 12))

plt.bar(accuracy_scores.keys(), accuracy_scores.values(), color=['lightblue', 'pink'])

plt.title('Model Accuracy Comparison')

plt.ylabel('Accuracy Score')

plt.ylim([0, 1]) # Set y-axis limit to 0-1 for accuracy

plt.show()

```

OUTPUT:

EXAMPLE 1:

Crop : maize

Irrigation_frequency : 2

EXAMPLE 2:

Crop : chickpeas

Irrigation_frequency : 4

CONCLUSION:

Through the analysis of environmental elements such as rainfall, temperature, and soil moisture, the machine learning-based smart irrigation system effectively optimizes water usage in agriculture. The machine learning approach promotes sustainable farming practices by increasing irrigation efficiency, decreasing water waste, and minimizing manual intervention. Even if the experiment shows encouraging results, bigger datasets, more sophisticated models, and IoT integration for real-time monitoring are possible for future enhancements. Addressing water scarcity and guaranteeing effective resource management in contemporary farming are made possible by this technique.