NUNNA LEEKHITH SRI KRISHNA

Climate-Aware Adaptation Strategy Prediction Using Machine Learning

Objective:

Develop a machine learning model that predicts the most suitable agricultural adaptation strategy based on climate, environmental, and regional factors.

This can help farmers or policy-makers automatically choose the best strategy to improve crop resilience and yield under changing climate conditions.

Size and Feactures of Dataset

```
% Load dataset
data = readtable("C:\Users\leekh\OneDrive - Amrita vishwa vidyapeetham\Git\5_climate_change_impact_on_agriculture_2024\climate_change_impact_on_agriculture_2024.csv")
```

```
data = 10000×15 table
```

...

	Year	Country	Region	Crop_Type	Average_Temperature_C
1	2001	'India'	'West Bengal'	'Corn'	1.5500
2	2024	'China'	'North'	'Corn'	3.2300
3	2001	'France'	'Ile-de-France'	'Wheat'	21.1100
4	2001	'Canada'	'Prairies'	'Coffee'	27.8500
5	1998	'India'	'Tamil Nadu'	'Sugarcane'	2.1900
6	2019	'USA'	'Midwest'	'Coffee'	17.1900
7	1997	'Argentina'	'Northeast'	'Fruits'	23.4600
8	2021	'Australia'	'New South Wales'	'Rice'	25.6300
9	2012	'India'	'Punjab'	'Wheat'	32.0800
10	2018	'Nigeria'	'North West'	'Barley'	21.2300
11	2006	'Nigeria'	'South East'	'Sugarcane'	-3.5700
12	1997	'France'	'Grand Est'	'Coffee'	34.3600
13	1993	'Russia'	'Northwestern'	'Vegetables'	19.0900
14	2003	'USA'	'Northeast'	'Barley'	14.7000

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```
% Size of dataset
[m, n] = size(data);
fprintf('Rows: %d, Columns: %d\n', m, n);
```

```
Rows: 10000, Columns: 15
```

```
% List all feature names
disp('Feature Names:');
```

```
Feature Names:
```

```
disp(data.Properties.VariableNames');
```

```
    {'Year'                      }
    {'Country'                   }
    {'Region'                    }
    {'Crop_Type'                 }
    {'Average_Temperature_C'     }
    {'Total_Precipitation_mm'    }
    {'CO2_Emissions_MT'          }
    {'Crop_Yield_MT_per_HA'      }
    {'Extreme_Weather_Events'    }
    {'Irrigation_Access_'        }
    {'Pesticide_Use_KG_per_HA'   }
    {'Fertilizer_Use_KG_per_HA'  }
    {'Soil_Health_Index'         }
    {'Adaptation_Strategies'     }
    {'Economic_Impact_Million_USD'}
```

Class Distribution

Read the Dataset

```
% Load the CSV dataset
data = readtable('C:\Users\leekh\OneDrive - Amrita vishwa
vidyapeetham\Git\5_climate_change_impact_on_agriculture_2024\climate_change_impact_o
n_agriculture_2024.csv');
```

Convert Target Column to Categorical

```
% Convert the target column to categorical if it isn’t already
data.Adaptation_Strategies = categorical(data.Adaptation_Strategies);
```

Get Class Counts

```
% Count number of samples per strategy
strategyCounts = countcats(data.Adaptation_Strategies);

% Get the strategy names
strategyNames = categories(data.Adaptation_Strategies);
```

Display Class Distribution

```
% Print the results
fprintf('Adaptation Strategy Distribution:\n');
```

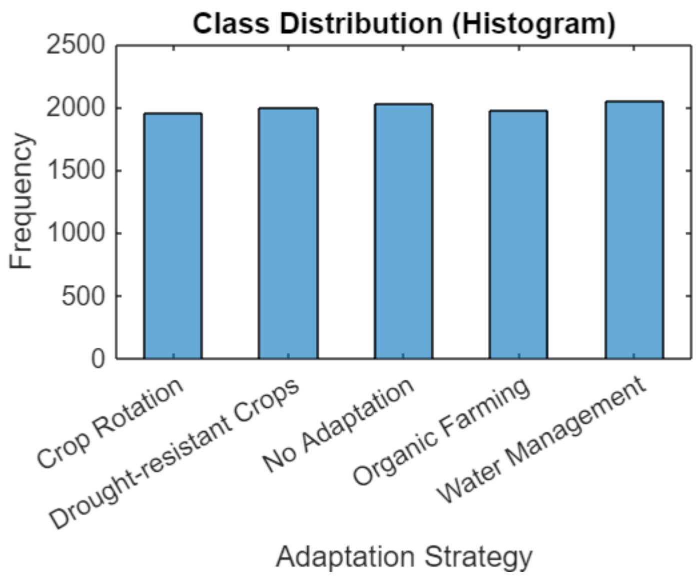
```
Adaptation Strategy Distribution:
```

```
for i = 1:length(strategyNames)
    fprintf('%s: %d samples\n', strategyNames{i}, strategyCounts(i));
end
```

```
Crop Rotation: 1957 samples
Drought-resistant Crops: 1995 samples
No Adaptation: 2024 samples
Organic Farming: 1975 samples
Water Management: 2049 samples
```

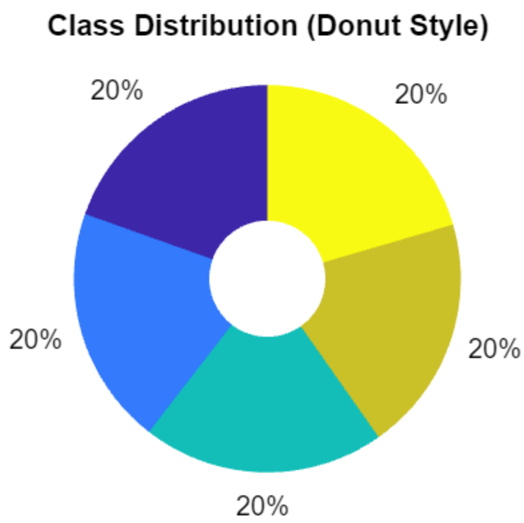
Stacked Histogram

```
figure;
histogram(data.Adaptation_Strategies, 'DisplayStyle','bar', 'BarWidth',0.5);
xlabel('Adaptation Strategy');
ylabel('Frequency');
title('Class Distribution (Histogram)');
```



Donut Chart

```
figure;
p = pie(strategyCounts);
title('Class Distribution (Donut Style)');
% Create hole
for i = 1:2:length(p)
    p(i).EdgeColor = 'none';
end
% Place white circle in center
hold on;
r = rectangle('Position',[-0.3,-0.3,0.6,0.6], 'Curvature',[1,1],
'FaceColor','white', 'EdgeColor','none');
hold off;
```



Preprocessing for Classification

Load the Dataset

```
% Read the dataset from CSV
data = readtable("C:\Users\leekh\OneDrive - Amrita vishwa
vidyapeetham\Git\5_climate_change_impact_on_agriculture_2024\climate_change_impact_o
n_agriculture_2024.csv")
```

```
data = 10000×15 table
```

...

	Year	Country	Region	Crop_Type	Average_Temperature_C
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14	2003	'USA'	'Northeast'	'Barley'	14.7000

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Convert Relevant Columns to Categorical

```
% Convert string-based columns to categorical
data.Country = categorical(data.Country);
data.Region = categorical(data.Region);
data.Crop_Type = categorical(data.Crop_Type);
data.Adaptation_Strategies = categorical(data.Adaptation_Strategies); % This is our
target
```

Handle Missing Data

```
% Show summary of missing values
disp('Missing value count per column:');
```

```
Missing value count per column:
```

```
disp(sum(ismissing(data)));
```

```
     0     0     0     0     0     0     0     0     0     0     0     0     0     0     0
```

```

% Option 1: Drop rows with missing values
data = rmmissing(data);

% (Option 2: Fill missing values — e.g., fill numeric with mean)
% data.Average_Temperature_C = fillmissing(data.Average_Temperature_C, 'movmean',
5);
```

Encode Categorical Features

```
% Label encode categorical variables
data.Region = grp2idx(data.Region);
data.Country = grp2idx(data.Country);
data.Crop_Type = grp2idx(data.Crop_Type);
```

Extract Features (X) and Labels (Y)

```
% Select features and label
X = data(:, {'Average_Temperature_C', 'Total_Precipitation_mm', ...
             'CO2_Emissions_MT', 'Extreme_Weather_Events', ...
             'Irrigation_Access_', 'Soil_Health_Index', ...
             'Crop_Type', 'Region'});  % Feel free to include Country too

Y = data.Adaptation_Strategies;
```

Convert Table to Matrix & Normalize Features

```
% Convert table to matrix and normalize features
X = normalize(table2array(X));  % Z-score normalization
```

Encode the Target Labels

```
% Convert the categorical target into numeric class labels
Y = grp2idx(Y);
```

Split into Train & Test Sets

```
% Create a partition (70% train, 30% test)
cv = cvpartition(size(X,1), 'HoldOut', 0.3);

XTrain = X(training(cv), :);
YTrain = Y(training(cv));
XTest = X(test(cv), :);
YTest = Y(test(cv));
```

Convert Training and Test Data into Tables

```
% Combine XTrain and YTrain into one table
trainTable = array2table([XTrain YTrain], ...
    'VariableNames', {'AvgTemp', 'Precip', 'CO2', 'ExtremeEvents', ...
                      'Irrigation', 'SoilHealth', 'CropType', 'Region',
'Strategy'});

% Combine XTest and YTest into one table
testTable = array2table([XTest YTest], ...
    'VariableNames', {'AvgTemp', 'Precip', 'CO2', 'ExtremeEvents', ...
                      'Irrigation', 'SoilHealth', 'CropType', 'Region',
'Strategy'});
```

Write the tables to CSV files

```
writetable(trainTable, 'train_data.csv');
writetable(testTable, 'test_data.csv');

disp("? Train and test sets saved as 'train_data.csv' and 'test_data.csv'");
```

```
? Train and test sets saved as 'train_data.csv' and 'test_data.csv'
```

Quality Check Before Training ML Model

Check for Missing Values

```
disp("Missing values per column:");
```

```
Missing values per column:
```

```
disp(sum(ismissing(data)));
```

```
     0     0     0     0     0     0     0     0     0     0     0     0     0     0     0
```

Check Class Distribution (Again)

```
tabulate(Y)  % shows class count, percentage
```

```
  Value    Count   Percent
      1     1957     19.57%
      2     1995     19.95%
      3     2024     20.24%
      4     1975     19.75%
      5     2049     20.49%
```

Check Feature Statistics

```
disp("Mean of features (should be ~0 after normalization):");
```

```
Mean of features (should be ~0 after normalization):
```

```
disp(mean(X));
```

```
   1.0e-14 *

   -0.0442    0.1432   -0.0217    0.0122    0.0638   -0.0956   -0.0069    0.0399
```

```

disp("Std deviation of features (should be ~1):");
```

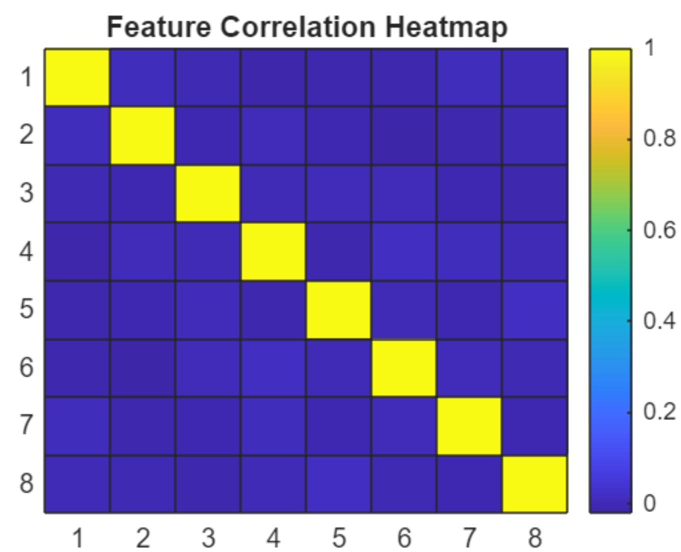
```
Std deviation of features (should be ~1):
```

```
disp(std(X));
```

```
    1.0000    1.0000    1.0000    1.0000    1.0000    1.0000    1.0000    1.0000
```

Correlation Heatmap

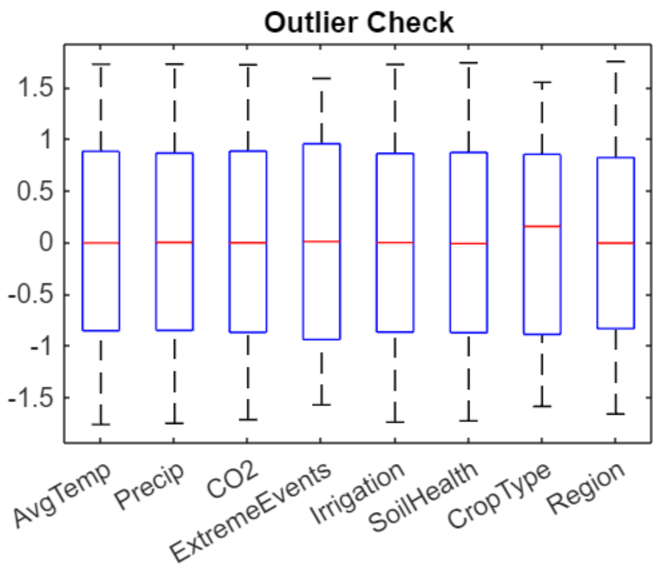
```
figure;
corrMatrix = corr(X);
heatmap(corrMatrix, 'Colormap', parula, 'Title', 'Feature Correlation Heatmap');
```



Outlier Visualization (Optional)

```
figure;
```

```
boxplot(X, 'Labels', {'AvgTemp', 'Precip', 'CO2', 'ExtremeEvents', ...
                      'Irrigation', 'SoilHealth', 'CropType', 'Region'});
title('Outlier Check');
```



Compare 5 Classifiers + Accuracy Leaderboard

```
% ==================== Setup ====================
models = {
    fitcecoc(XTrain, YTrain),           'SVM (ECOC)';
    fitcknn(XTrain, YTrain),            'KNN';
    fitctree(XTrain, YTrain),           'Decision Tree';
    fitcensemble(XTrain, YTrain),       'Random Forest';
    fitcnb(XTrain, YTrain),             'Naive Bayes';
};


% Initialize results storage
accuracies = zeros(size(models, 1), 1);

% ==================== Train & Evaluate ====================
for i = 1:size(models, 1)
    model = models{i,1};
    name = models{i,2};

    % Predict on test set
    predictions = predict(model, XTest);

    % Calculate accuracy
    acc = sum(predictions == YTest) / numel(YTest);
    accuracies(i) = acc;

    % Display individual result
    fprintf('□ %s Accuracy: %.2f%%\n', name, acc * 100);
```

```
end
```

```
� SVM (ECOC) Accuracy: 19.67%
� KNN Accuracy: 18.93%
� Decision Tree Accuracy: 18.90%
� Random Forest Accuracy: 18.73%
� Naive Bayes Accuracy: 19.03%
```

```
% ==================== Leaderboard ====================
% Display as sorted leaderboard
[sortedAcc, idx] = sort(accuracies, 'descend');
sortedNames = models(idx, 2);

fprintf('\n� Accuracy Leaderboard:\n');
```

```
� Accuracy Leaderboard:
```

```
for i = 1:length(sortedAcc)
    fprintf('%d. %s - %.2f%%\n', i, sortedNames{i}, sortedAcc(i) * 100);
end
```

```
1. SVM (ECOC) - 19.67%
2. Naive Bayes - 19.03%
3. KNN - 18.93%
4. Decision Tree - 18.90%
5. Random Forest - 18.73%
```

Repair the data

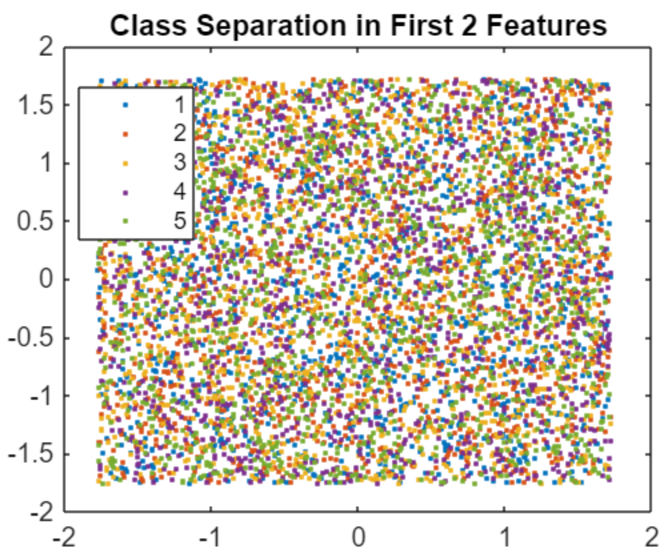
Labels Might Not Be Properly Encoded

```
unique(YTrain)
```

```
ans = 5×1
     1
     2
     3
     4
     5
```

Features Might Be Useless for Classification

```
gscatter(XTrain(:,1), XTrain(:,2), YTrain);
title("Class Separation in First 2 Features");
```



Model Complexity Needs Tuning

```
% Tune Random Forest
rf = fitcensemble(XTrain, YTrain, 'NumLearningCycles', 100);

% Tune KNN
knn = fitcknn(XTrain, YTrain, 'NumNeighbors', 7);

% Tune SVM (ECOC + linear kernel)
svm = fitcecoc(XTrain, YTrain, 'Learners', templateSVM('KernelFunction','linear'));
```

Convert Labels to Numeric (If Not Already)

```
YTrain = grp2idx(YTrain);
YTest = grp2idx(YTest);
```

Upgrade Random Forest

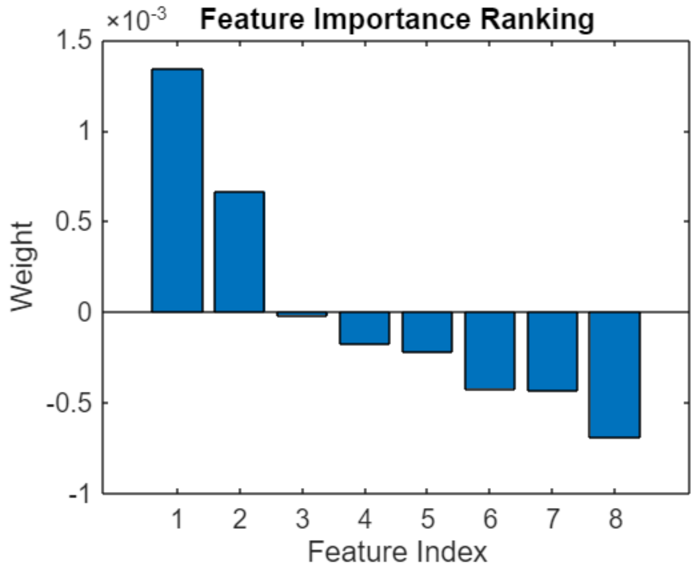
```
rfModel = fitcensemble(XTrain, YTrain, ...
    'NumLearningCycles', 200, ...
    'Method', 'Bag');
YPred = predict(rfModel, XTest);
acc = sum(YPred == YTest) / numel(YTest);
fprintf("� Upgraded RF Accuracy: %.2f%%\n", acc*100);
```

```
� Upgraded RF Accuracy: 20.17%
```

Feature Selection

```
% Rank features using relieff
[idx, weights] = relieff(XTrain, YTrain, 10);
bar(weights(idx));
title('Feature Importance Ranking');
xlabel('Feature Index');
```

```
ylabel('Weight');
```




```
% Use top N features (e.g., 5)
XTrainTop = XTrain(:, idx(1:5));
XTestTop = XTest(:, idx(1:5));
```

� **Classification is not a good fit** for this dataset **in its current form**.

� **Test**	� **What Happened**	� **What It Means**
Model Accuracy	~20% even after tuning	Basically guessing
Scatter Plot	Total visual noise	Features don’t separate classes
Feature Impact	Likely all classes have similar values	Models can’t “learn” the labels
Class Balance	Perfectly balanced	Not the problem
Upgraded Models	Still flop	Not about the model, it's the data-task mismatch

That's It