

Crop analysis and pesticides Recommendation system

Mr. Devdas - Guide





MINI PROJECT GROUP 7

B. SAI BHARGAV

20QM1A6608 3RD CSM KGRCET

03 P. VENILLA

20QM1A6639 3RD CSM KGRCET O2 CH. LIKITHA

20QM1A6609 3RD CSM KGRCET

04 SHAHNAWAAZ

20QM1A6630 3RD CSM KGRCET



1) Crop Prediction: Crop Prediction Data, CSV file format

	Α	В	С	D	Е	F	G	Н	1	J	K	L	М	N	0	Р	Q	R	S	Т	U	V	W
Dist	t Code Ye	ar	State Code	State Nam E	ist Nam	e RICE AREA	RICE PROE	RICE YIELE V	VHEAT AF V	VHEAT PE	WHEAT YII	KHARIF SO	KHARIF SO	KHARIF SO	RABI SORG	RABI SORE	RABI SORG	SORGHUN	SORGHUN	SORGHUN	PEARL MIL	PEARL MIL	PEARL MIL M.
2	1	1966	14	Chhattisga [Ourg	548	185	337.59	44	20	454.55	0.6	0.4	666.67	0	0	0	0.6	0.4	666.67	0	0	0
3	1	1967	14	Chhattisga [Ourg	547	409	747.71	50	26	520	1.1	0.9	818.18	0	0	0	1.1	0.9	818.18	0	0	0
ļ.	1	1968	14	Chhattisga [Ourg	556.3	468	841.27	53.7	30	558.66	0.5	0.4	800	0	0	0	0.5	0.4	800	0	0	0
,	1	1969	14	Chhattisga E	Ourg	563.4	400.8	711.4	49.4	26.5	536.44	0.8	0.6	750	0	0	0	0.8	0.6	750	0	0	0
5	1	1970	14	Chhattisga [Ourg	571.6	473.6	828.55	44.2	29	656.11	0.9	0.6	666.67	0	0	0	0.9	0.6	666.67	0	0	0
,	1	1971	14	Chhattisga [Ourg	581.8	412.9	709.69	44.4	25.8	581.08	0.3	0.2	666.67	0	0	0	0.3	0.2	666.67	0	0	0
3	1	1972	14	Chhattisga [Ourg	582.2	381	654.41	39.6	20.6	520.2	0.3	0.3	1000	0	0	0	0.3	0.3	1000	0	0	0
9	1	1973	14	Chhattisga E	Ourg	600	471.9	786.5	37.3	18.6	498.66	0.2	0.2	1000	0	0	0	0.2	0.2	1000	0	0	0
0	1	1974	14	Chhattisga [Ourg	587.4	219	372.83	36.5	22.4	613.7	0.5	0.4	800	0	0	0	0.5	0.4	800	0	0	0
1	1	1975	14	Chhattisga [Ourg	598.3	454	758.82	49.2	27.8	565.04	0.2	0.2	1000	0	0	0	0.2	0.2	1000	0	0	0
2	1	1976	14	Chhattisga E	Ourg	593.6	327.1	551.04	46.9	10	213.22	0.1	0.1	1000	0	0	0	0.1	0.1	1000	0	0	0
3	1	1977	14	Chhattisga [Ourg	600.7	572.4	952.89	53.1	27.1	510.36	0.1	0.1	1000	0	0	0	0.1	0.1	1000	0	0	0
4	1	1978	14	Chhattisga E	Ourg	612.5	362.2	591.35	48.7	25.6	525.67	0.1	0.1	1000	0	0	0	0.1	0.1	1000	0	0	0
5	1	1979	14	Chhattisga [Ourg	616.8	330.6	535.99	44.6	17.8	399.1	0.5	0.5	1000	0	0	0	0.5	0.5	1000	0	0	0
6	1	1980	14	Chhattisga E	Ourg	634.9	515.6	812.1	44.1	33.6	761.9	0.2	0.2	1000	0	0	0	0.2	0.2	1000	0	0	0
7	1	1981	14	Chhattisga E	Ourg	630	506.9	804.6	41.5	23.6	568.67	0.2	0.2	1000	0	0	0	0.2	0.2	1000	0	0	0
8	1	1982	14	Chhattisga [Ourg	627.9	513.3	817.49	41.1	23.9	581.51	0.1	0.1	1000	0	0	0	0.1	0.1	1000	0	0	0
9	1	1983	14	Chhattisga E	Ourg	626.7	711	1134.51	39.9	20.6	516.29	0.1	0.1	1000	0	0	0	0.1	0.1	1000	0	0	0
0	1	1984	14	Chhattisga E	Ourg	632.2	563.8	891.81	40.5	19.9	491.36	0.3	0.3	1000	0	0	0	0.3	0.3	1000	0	0	0
1	1	1985	14	Chhattisga [Ourg	630.8	699.8	1109.38	39.4	21	532.99	0.3	0.2	666.67	0	0	0	0.3	0.2	666.67	0	0	0
2	1	1986	14	Chhattisga [Ourg	643	525	816.49	37	24	648.65	0.2	0.1	500	0	0	0	0.2	0.1	500	0	0	0
3	1	1987	14	Chhattisga E	Ourg	648	523	807.1	43	23	534.88	0.3	0.2	666.67	0	0	0	0.3	0.2	666.67	0	0	0
4	1	1988	14	Chhattisga D	Ourg	652.7	549.7	842.19	43.7	20.2	462.24	0.1	0.1	1000	0	0	0	0.1	0.1	1000	0	0	0
5	1	1989	14	Chhattisga [Ourg	660.2	457.3	692.67	43.8	22.7	518.26	0.1	0.1	1000	0	0	0	0.1	0.1	1000	0	0	0
6	1	1990		Chhattisga [682.9	806.8	1181.43	36.2	24.8	685.08	0.5	0.4	800	0	0	0	0.5	0.4	800	0	0	0
7	1	1991	14	Chhattisga E	Ourg	680.8	773.6	1136.31	34.8	21.6	620.69	2.3	1.8	782.61	0	0	0	2.3	1.8	782.61	0	0	0
0		1003	1.4	Chimina		C00	777 1	1120.0	FC 4	20.5	205.42			000 00	^	^	^		- 1	000 00	^	^	0
<	>	Crop	Prediction	Data	+									:	4								•



2) Crop Disease Classification: Crop Disease Classification Data, CSV file format







3) Crop Clustering:

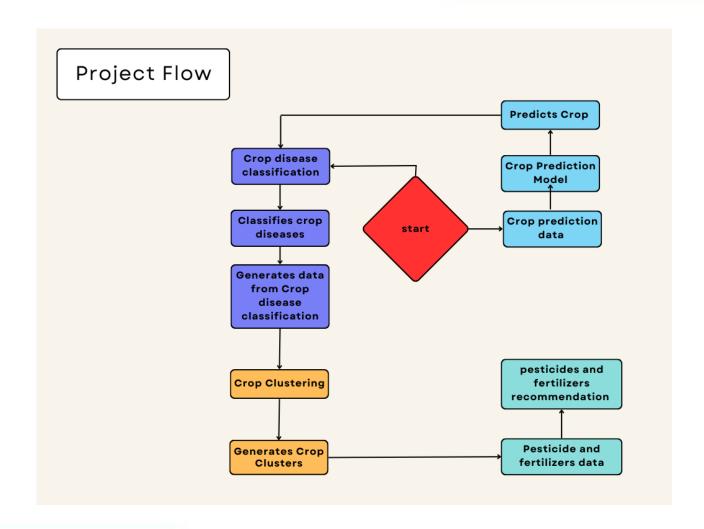
In crop clustering, we use data that we have extracted from the crop disease classification.



4) Pesticides and Fertilizers Recommendation: P&F Data, CSV file format

					4	/ \	U		
1	Entity	Code	Year	Nutrient	1	Entity	Code	Year	Pesticides (to
2	Afghanistan	AFG	1961	0.13	2	Africa (FA	AO)	1990	65944.26
3	Afghanistan	AFG	1962	0.13	3	Africa (FA	AO)	1991	62723.2
4	Afghanistan	AFG	1963	0.13	4	Africa (FA	AO)	1992	54428.07
5	Afghanistan	AFG	1964	0.13	5	Africa (FA	AO)	1993	49620.53
6	Afghanistan	AFG	1965	0.13	6	Africa (FA	AO)	1994	51095.37
7	Afghanistan	AFG	1966	0.13	7	Africa (FA	4O)	1995	56939.78
8	Afghanistan	AFG	1967	1.13	8	Africa (FA	AO)	1996	58563.56
9	Afghanistan	AFG	1968	1.75	9	Africa (FA	AO)	1997	59473.66
10	Afghanistan	AFG	1969	1.88	10	Africa (FA	AO)	1998	60770.25
11	Afghanistan	AFG	1970	2	11	Africa (FA	AO)	1999	63027.14
12	Afghanistan	AFG	1971	1.84	12	Africa (FA	AO)	2000	63894.15
13	Afghanistan	AFG	1972	1.99	13	Africa (FA	AO)	2001	64523.1
14	Afghanistan	AFG	1973	2.2	14	Africa (FA	AO)	2002	67516.16
15	Afghanistan	AFG	1974	3.01	15	Africa (FA	AO)	2003	69697.31
16	Afghanistan	AFG	1975	3.44	16	Africa (FA	AO)	2004	73268.59
17	Afghanistan	AFG	1976	3.81	17	Africa (FA	AO)	2005	71312.94
18	Afghanistan	AFG	1977	4.6	18	Africa (FA	AO)	2006	77401.08
19	Afghanistan	AFG	1978	4.41	19	Africa (FA	(O)	2007	75657.45
20	Afghanistan	AFG	1979	4.13	20	Africa (FA	AO)	2008	79274.89







1) Crop Prediction:

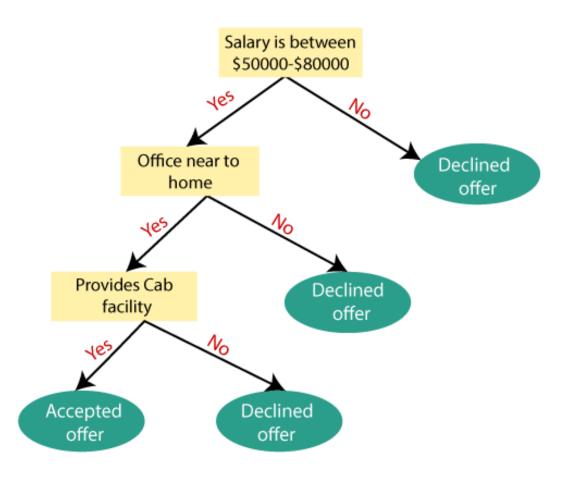
1) Decision Tree

- **Step-1**: Begin the tree with the root node, says S, which contains the complete dataset.
- •Step-2: Find the best attribute in the dataset using Attribute Selection Measure (ASM).
- •Step-3: Divide the S into subsets that contains possible values for the best attributes.
- •Step-4: Generate the decision tree node, which contains the best attribute.
- •Step-5: Recursively make new decision trees using the subsets of the dataset created in step -3. Continue this process until a stage is reached where you cannot further classify the nodes and called the final node as a leaf node.

Example

- 1) Suppose there is a candidate who has a job offer and wants to decide whether he should accept the offer or Not.
- **2)** So, to solve this problem, the decision tree starts with the root node (Salary attribute by ASM).
- **3)** The root node splits further into the next decision node (distance from the office) and one leaf node based on the corresponding labels.
- **4)** The next decision node further gets split into one decision node (Cab facility) and one leaf node.
- **5)** Finally, the decision node splits into two leaf nodes (Accepted offers and Declined offer).







1) Crop Prediction:

2) Random Forest:

Step-1: Select random K data points from the training set.

Step-2: Build the decision trees associated with the selected data points (Subsets).

Step-3: Choose the number N for decision trees that you want to build.

Step-4: Repeat Step 1 & 2.

Step-5: For new data points, find the predictions of each decision tree, and assign the new data points to the category that wins the majority votes.

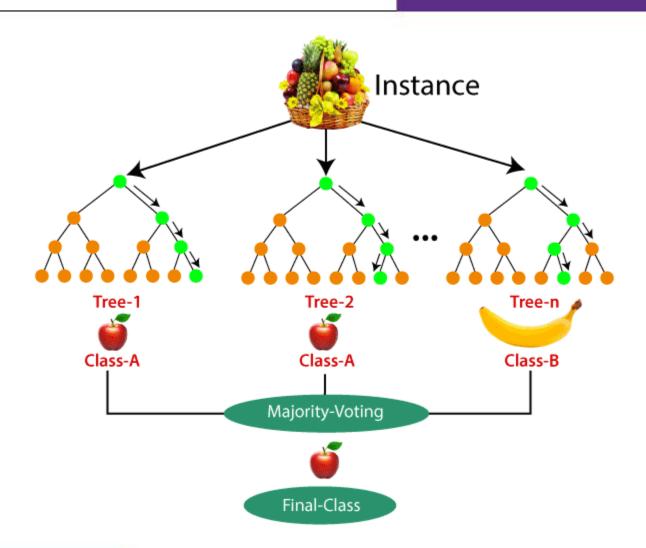
Example:

Suppose there is a dataset that contains multiple fruit images.

So, this dataset is given to the Random forest classifier. The dataset is divided into subsets and given to each decision tree.

During the training phase, each decision tree produces a prediction result when a new data point occurs, then based on the majority of results, the Random Forest classifier predicts the final decision







2) Crop disease classification: Example:

Conventional Neural Networks:

import the necessary libraries set the parameter define the kernel Load the image and plot it.

Reformat the image

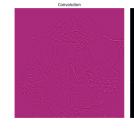
Apply convolution layer operation and plot the output image.

Apply activation layer operation and plot the output image.

Apply pooling layer operation and plot the output image.













Example:

3) Crop Clustering:

1)K-Means Clustering:

Step-1: Select the number K to decide the number of clusters.

Step-2: Select random K points or centroids. (It can be other from the input dataset).

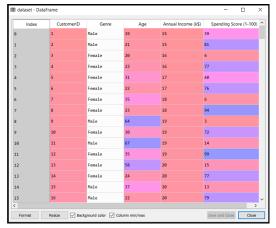
Step-3: Assign each data point to their closest centroid, which will form the predefined K clusters.

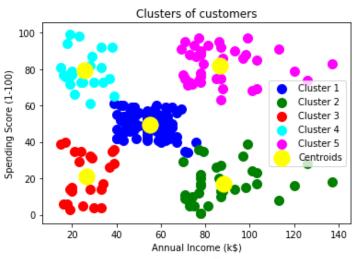
Step-4: Calculate the variance and place a new centroid of each cluster.

Step-5: Repeat the third steps, which means reassign each datapoint to the new closest centroid of each cluster.

Step-6: If any reassignment occurs, then go to step-4 else go to FINISH.

Step-7: The model is ready.







3) Crop Clustering:

2) Fuzzy Clustering:

Step 1: Initialize the data points into the desired number of clusters randomly.

Step 2: Find out the centroid.

Step 3: Find out the distance of each point from the centroid.

Step 4: Updating membership values.

Step 5: Repeat the steps(2-4) until the constant values are obtained for the membership values or the difference is less than the tolerance value

Step 6: Defuzzify the obtained membership values.

Example:

Cluster (1, 3) (2, 5) (4, 8) (7, 9)

1) 0.8 0.7 0.2 0.1

2) 0.2 0.3 0.8 0.9

Cluster Centers:

[[0.42363557 0.68304616]

[0.52768166 0.38180987]

[0.39967863 0.31042639]]

Cluster Membership:

 $\begin{bmatrix} 1 & 0 & 1 & 2 & 1 & 0 & 0 & 2 & 0 & 2 & 1 & 0 & 0 & 0 & 1 & 2 & 1 & 1 & 0 & 2 & 2 & 1 & 1 & 2 & 0 & 1 & 0 \\ 0 & 2 & 0 & 2 & 1 & 1 & 0 & 0 & 1 & 1 & 1 & 1 & 2 & 2 & 0 & 1 & 1 & 2 & 0 & 0 & 1 & 1 & 2 & 2 & 0 & 1 & 1 & 2 & 0 & 0 \\ 1 & 0 & 2 & 0 & 0 & 2 & 0 & 0 & 1 & 1 & 1 & 1 & 2 & 2 & 0 & 1 & 1 & 0 & 0 & 2 & 2 & 2 & 0 & 1 & 1 & 2 & 0 & 0 \\ \end{bmatrix}$

0210100

120022110210221102102102220102]



4) Pesticide and Fertilizer recommendation

1) Collabarative Based filtering:

Step 1: Finding the similarity of users to the target user U.

Step 2: Prediction of missing rating of an item

Example: Consider a matrix that shows four users Alice, U1, U2 and U3 rating on different news apps. The rating range is from 1 to 5 on the basis of users' likability of the news app.

Step 1: Calculating the similarity between Alice and all the other users At first we calculate the averages of the ratings of all the user excluding I5 as it is not rated by Alice.

Step 2:Predicting the rating of the app not rated by Alice Now, we predict Alice's rating for BBC News App.



Example:

Name	Inshor BBC(I5	` '	HT(I2)	NYT(I3)	TOI(I4)	
Alice	5	4	1	4	?	
U1	3	1	2	3	3	
U2	4	3	4	3	5	
U3	3	3	1	5	4	

Step 1:

Name	Inshorts(l1)	HT(I2)	NYT(I3)	TOI(I4)
Alice	1.5	0.5	-2.5	0.5	
U1	0.75	-1.25	-0.25	0.75	
U2	0.5	-0.5	0.5	-0.5	
U3	0	0	-2	2	

Step 2:

$$[Tex]r_{(Alice,I5)}=3.5 + \frac{(0.301*0.75)+(-0.33*1.5)+(0.707*1)}{|0.301|+|-0.33|+|0.707|}=3.83\\ newline$$



4) Pesticide and Fertilizer recommendation

2) Content Based filtering:

Content-based filtering makes recommendations by using keywords and attributes assigned to objects in a database (e.g., items in an online marketplace) and matching them to a user profile. The user profile is created based on data derived from a user's actions, such as purchases, ratings (likes and dislikes), downloads, items searched for on a website and/or placed in a cart, and clicks on product links.

Example: suppose you're recommending accessories to a user that just purchased a smartphone from your website and has previously bought smartphone accessories. Aside from keywords such as the smartphone manufacturer, make, and model, the user profile indicates prior purchases include phone holders with sleeves for credit cards. Based on this information, the recommender system may suggest similar phone holders for the new phone with attributes such as an RFID blocking fabric layer to help prevent unauthorized credit card scanning. In this example, the user would expect recommendations for similar phone holders, but the RFID blocking feature may be something they didn't expect yet appreciate.



Mank