

## **Crop analysis and Disease Classification System**

Mr. Devdas - Guide





### MINI PROJECT GROUP 7

B. SAI BHARGAV

20QM1A6608 3<sup>RD</sup> CSM KGRCET

03 P. VENILLA

20QM1A6639 3<sup>RD</sup> CSM KGRCET O2 CH. LIKITHA

20QM1A6609 3<sup>RD</sup> CSM KGRCET

04 SHAHNAWAAZ

20QM1A6630 3<sup>RD</sup> CSM KGRCET



#### **Problem Statement:**

- Many farmers in India don't know what type of crops they need to grow on their farm depending on their soil conditions and the water resources available in their village.
- Due to these unknown conditions, they try to grow different types of crops but fail to harvest a good yield.
- > They don't know what type of disease their crops are suffering with.
- They don't know what type of pesticides, insecticides and fertilizers that crops in the farm require.
- This makes them to spend money on large amounts of fertilizer's, pesticides, and insecticides unnecessarily also damages crop which even don't require.



#### **DATASETS:**

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

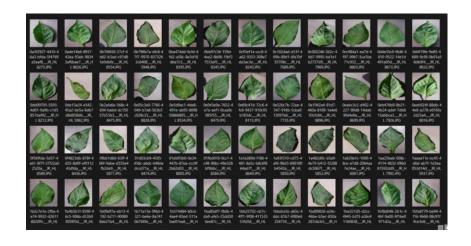
Α	В		D	E	F	G	Н
N	Р	K	temperature	humidity	ph	rainfall	label
90	42	43	20.87974371	82.00274423	6.502985292	202.9355362	rice
85	58	41	21.77046169	80.31964408	7.038096361	226.6555374	rice
60	55	44	23.00445915	82.3207629	7.840207144	263.9642476	rice
74	35	40	26.49109635	80.15836264	6.980400905	242.8640342	rice
78	42	42	20.13017482	81.60487287	7.628472891	262.7173405	rice
69	37	42	23.05804872	83.37011772	7.073453503	251.0549998	rice
69	55	38	22.70883798	82.63941394	5.70080568	271.3248604	rice
94	53	40	20.27774362	82.89408619	5.718627178	241.9741949	rice
89	54	38	24.51588066	83.5352163	6.685346424	230.4462359	rice
68	58	38	23.22397386	83.03322691	6.336253525	221.2091958	rice
91	53	40	26.52723513	81.41753846	5.386167788	264.6148697	rice
90	46	42	23.97898217	81.45061596	7.50283396	250.0832336	rice
78	58	44	26.80079604	80.88684822	5.108681786	284.4364567	rice
93	56	36	24.01497622	82.05687182	6.98435366	185.2773389	rice
94	50	37	25.66585205	80.66385045	6.94801983	209.5869708	rice
60	48	39	24.28209415	80.30025587	7.042299069	231.0863347	rice
85	38	41	21.58711777	82.7883708	6.249050656	276.6552459	rice
91	35	39	23.79391957	80.41817957	6.970859754	206.2611855	rice
77	38	36	21.8652524	80.1923008	5.953933276	224.5550169	rice
88	35	40	23.57943626	83.58760316	5.85393208	291.2986618	rice
89	45	36	21.32504158	80.47476396	6.442475375	185.4974732	rice
76	40	43	25.15745531	83.11713476	5.070175667	231.3843163	rice
67	59	41	21.94766735	80.97384195	6.012632591	213.3560921	rice
83	41	43	21.0525355	82.67839517	6.254028451	233.1075816	rice
98	47	37	23.48381344	81.33265073	7.375482851	224.0581164	rice
66	53	41	25.0756354	80.52389148	7.778915154	257.0038865	rice

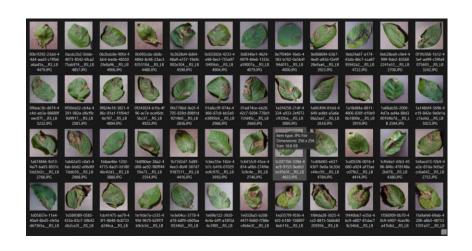
27	21	30	35.3915464	52.48823147	5.061081874	91.22881052	mango
22	38	31	31.53356352	53.06009323	5.821106036	98.57025046	mango
22	18	31	30.7645515	47.93791463	5.956027059	90.38503469	mango
28	23	28	30.01821337	50.0983181	5.676032581	96.08745082	mango
7	31	27	31.32863689	47.59319575	6.524114355	94.67344737	mango
29	34	26	33.88004781	54.39416048	6.273953676	89.29147581	mango
8	37	33	28.07802689	54.9640534	6.128167757	97.45373619	mango
39	16	27	35.53845018	52.94641947	4.934964765	91.54560427	mango
40	24	25	28.70595247	50.44030129	5.445008416	95.8946444	mango
19	38	26	31.48451729	48.77926304	4.525722333	93.17221967	mango
21	21	30	27.69819273	51.41593238	5.403908328	100.7720705	mango
22	18	33	30.41235793	52.48100602	6.621623545	93.92375879	mango
31	20	30	32.17752026	54.01352682	6.207495815	91.88766069	mango
18	26	31	32.6112614	47.74916499	5.418475257	91.10190759	mango
24	130	195	29.99677232	81.54156612	6.112305667	67.12534492	grapes
13	144	204	30.7280404	82.42614055	6.092241627	68.38135469	grapes
22	123	205	32.44577836	83.88504863	5.896343436	68.73932528	grapes
36	125	196	37.46566825	80.65968681	6.15526103	66.83872293	grapes
24	131	196	22.03296178	83.74372787	5.732453638	65.34440794	grapes
2	123	198	39.64851881	82.21079946	6.253034534	70.39906054	grapes
35	140	197	16.77557314	82.75241875	6.106190557	66.76285469	grapes
11	122	195	12.14190714	83.56812483	5.647202395	69.63122027	grapes
6	123	203	12.7567962	81.62497448	6.130310493	66.77844567	grapes
17	134	204	39.04071989	80.18393287	6.499604931	73.88467027	grapes
25	130	197	39.70772192	82.68593454	5.554831977	74.91506217	grapes
27	145	205	9.467960445	82.29335466	5.800242694	66.02765219	grapes
9	122	201	29.58748357	80.91934392	5.570290539	68.06417307	grapes



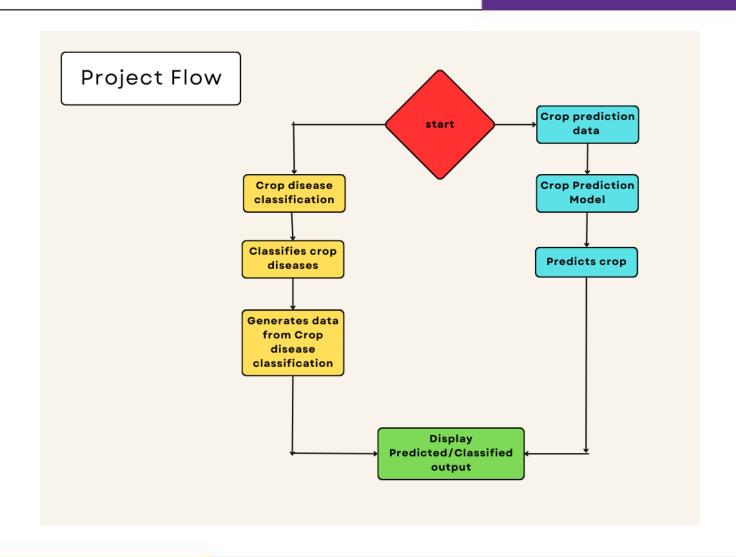
#### **DATASETS:**

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











#### **MODULES:**

## 1) Crop Prediction:

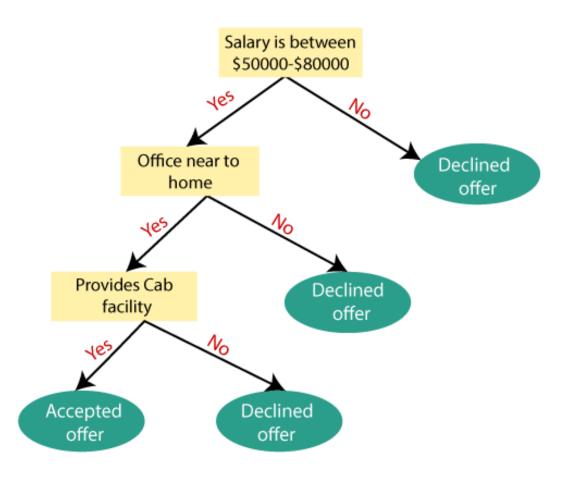
#### 1) Decision Tree

- **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).







#### **MODULES:**

## 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.

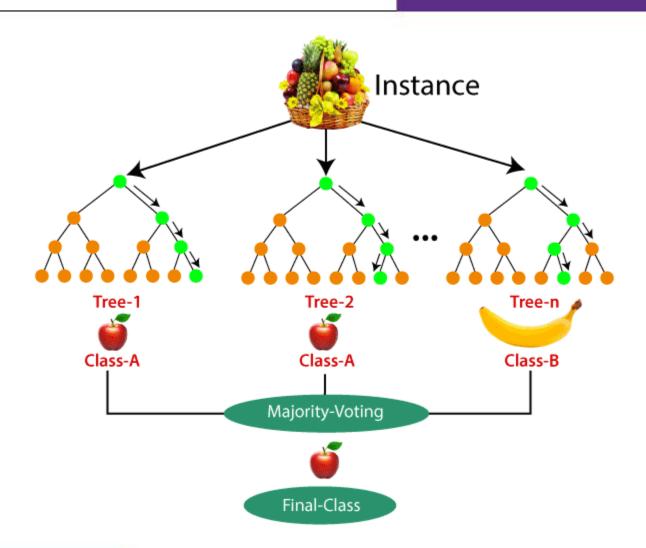
#### **Example:**

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







#### **MODULES:**

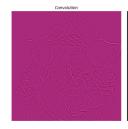
## 2) Crop disease classification: Example:

#### **Conventional Neural Networks:**

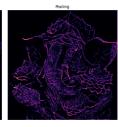
- VGG16
- Import the libraries for VGG16.
- Create an object for training and testing data.
- Initialize the model,
- Pass the data to the dense layer.
- Compile the model.
- Import libraries to monitor and control training.
- Visualize the training/validation data.
- Test your model.













#### **Conclusion:**

In conclusion, the project focused on crop prediction and disease classification has yielded promising results and holds significant potential for the agricultural industry. By leveraging machine learning algorithms and utilizing key factors such as soil conditions, weather data, and other parameters, the project successfully developed models for predicting the optimal crop type to be grown and classifying diseases in potatoes, peppers, and tomatoes.

The innovative aspect of the project lies in its ability to provide accurate recommendations based on data analysis, enabling farmers to make informed decisions regarding crop selection and disease management. The usability and acceptance of the innovation among the target group, primarily farmers and agricultural stakeholders, have been positive, indicating its practical relevance in the market.

The project has demonstrated economic viability by optimizing resource allocation, reducing costs, increasing crop yield, and improving market access for farmers. It has the potential to generate profits through cost savings, increased productivity, and value-added services. Furthermore, the innovation promotes environmental sustainability by encouraging sustainable farming practices, reducing chemical usage, and conserving biodiversity.



#### **Result:**

The result of the project is a set of predictive models for crop selection and disease classification in potatoes, peppers, and tomatoes. These models have been trained and validated using relevant data sources, achieving satisfactory accuracy levels in their predictions. The prototype or proof-of-concept (PoC) has been developed and demonstrated its functionality in providing actionable insights to farmers.

The project has shown its potential to address the market's need for accurate crop predictions and disease classifications, empowering farmers with valuable information to optimize their farming practices. The project's success in achieving the stated objectives and delivering tangible benefits to the agricultural industry is a testament to its value and potential impact.

Overall, the project has laid a strong foundation for a valuable product that can revolutionize crop selection and disease management in agriculture, contributing to improved yields, reduced costs, and sustainable farming practices.



Mank