Imports 👇

In [1]:
```
import pandas
import numpy
from sklearn import svm
from sklearn.metrics import confusion_matrix,classification_report
import seaborn
import matplotlib.pyplot as pyplot
```

👇 *setting the matplotlib configurations*

In [2]:
```
%matplotlib inline
pyplot.rcParams["figure.figsize"] = (15, 12)
```

Data Reading 👇

In [3]:
```
data=pandas.read_csv('./Crop_recommendation.csv')
```

👇 cheking the columns, data, data type information, correlation between attributes

In [4]:
```
data.columns
```

Out[4]:
```
Index(['N', 'P', 'K', 'temperature', 'humidity', 'ph', 'rainfall', 'label'], dtype='object')
```

In [5]:
```
data
```

Out[5]:

	N	P	K	temperature	humidity	ph	rainfall	label
0	90	42	43	20.879744	82.002744	6.502985	202.935536	rice
1	85	58	41	21.770462	80.319644	7.038096	226.655537	rice
2	60	55	44	23.004459	82.320763	7.840207	263.964248	rice
3	74	35	40	26.491096	80.158363	6.980401	242.864034	rice
4	78	42	42	20.130175	81.604873	7.628473	262.717340	rice
...	...	...	...	...	...	...	...	...
2195	107	34	32	26.774637	66.413269	6.780064	177.774507	coffee
2196	99	15	27	27.417112	56.636362	6.086922	127.924610	coffee
2197	118	33	30	24.131797	67.225123	6.362608	173.322839	coffee
2198	117	32	34	26.272418	52.127394	6.758793	127.175293	coffee
2199	104	18	30	23.603016	60.396475	6.779833	140.937041	coffee

2200 rows × 8 columns

In [6]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2200 entries, 0 to 2199
Data columns (total 8 columns):
 #   Column       Non-Null Count  Dtype  
---  ------       --------------  -----  
 0   N            2200 non-null   int64  
 1   P            2200 non-null   int64  
 2   K            2200 non-null   int64  
 3   temperature  2200 non-null   float64
 4   humidity     2200 non-null   float64
 5   ph           2200 non-null   float64
 6   rainfall     2200 non-null   float64
 7   label        2200 non-null   object 
dtypes: float64(4), int64(3), object(1)
memory usage: 137.6+ KB
```

In [7]:
```
data.describe()
```

Out[7]:

	N	P	K	temperature	humidity	ph	rainfall
count	2200.000000	2200.000000	2200.000000	2200.000000	2200.000000	2200.000000	2200.000000
mean	50.551818	53.362727	48.149091	25.616244	71.481779	6.469480	103.463655
std	36.917334	32.985883	50.647931	5.063749	22.263812	0.773938	54.958389
min	0.000000	5.000000	5.000000	8.825675	14.258040	3.504752	20.211267
25%	21.000000	28.000000	20.000000	22.769375	60.261953	5.971693	64.551686
50%	37.000000	51.000000	32.000000	25.598693	80.473146	6.425045	94.867624
75%	84.250000	68.000000	49.000000	28.561654	89.948771	6.923643	124.267508
max	140.000000	145.000000	205.000000	43.675493	99.981876	9.935091	298.560117

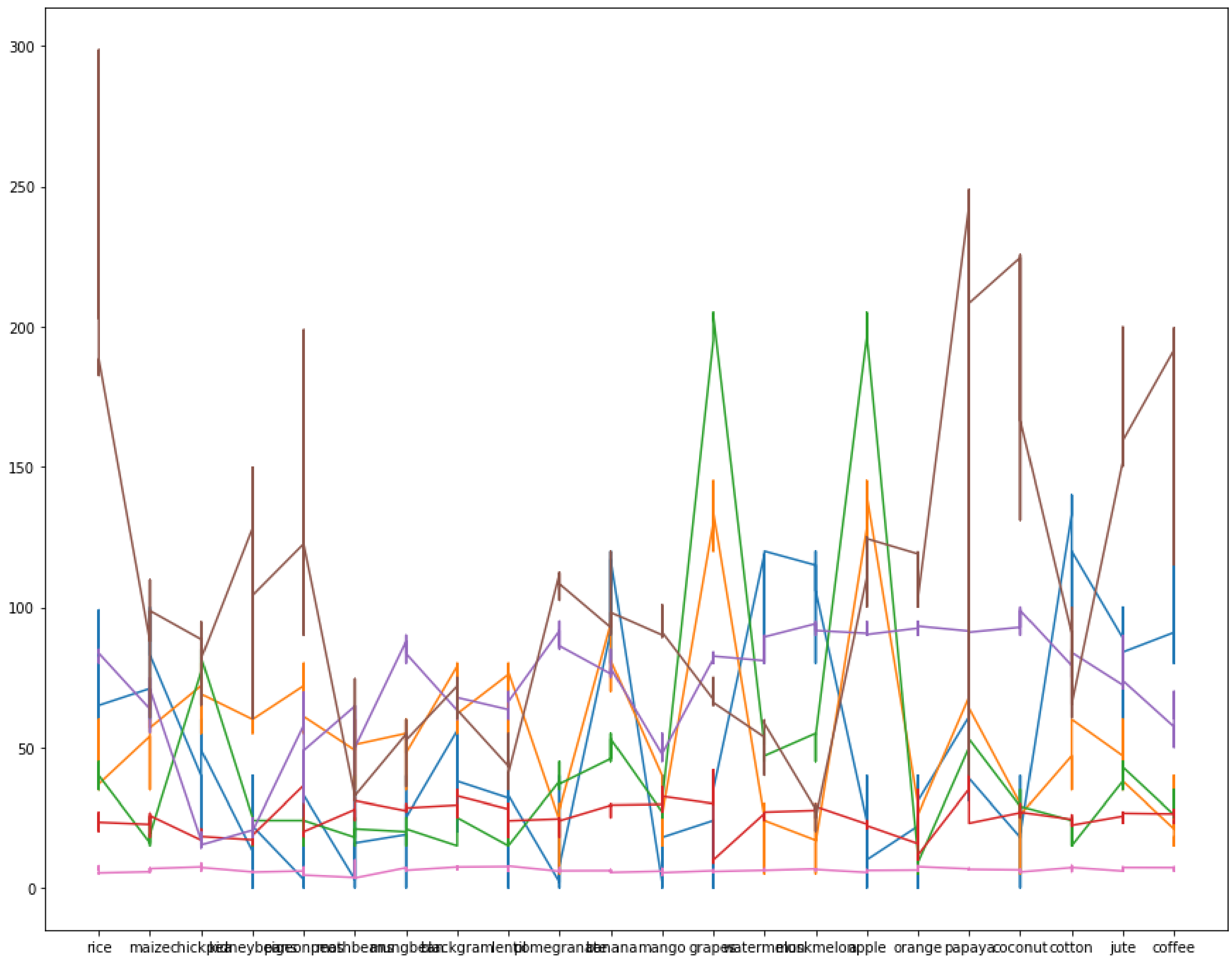
In [8]:
```
data.corr()
```

Out[8]:

	N	P	K	temperature	humidity	ph	rainfall
N	1.000000	-0.231460	-0.140512	0.026504	0.190688	0.096683	0.059020
P	-0.231460	1.000000	0.736232	-0.127541	-0.118734	-0.138019	-0.063839
K	-0.140512	0.736232	1.000000	-0.160387	0.190859	-0.169503	-0.053461
temperature	0.026504	-0.127541	-0.160387	1.000000	0.205320	-0.017795	-0.030084
humidity	0.190688	-0.118734	0.190859	0.205320	1.000000	-0.008483	0.094423
ph	0.096683	-0.138019	-0.169503	-0.017795	-0.008483	1.000000	-0.109069
rainfall	0.059020	-0.063839	-0.053461	-0.030084	0.094423	-0.109069	1.000000

In [9]:
```
pyplot.plot(data['label'],data[['N','P','K','temperature','humidity','rainfall','ph']])
```

Out[9]:
```
[<matplotlib.lines.Line2D at 0x2980773da30>,
 <matplotlib.lines.Line2D at 0x2980773d940>,
 <matplotlib.lines.Line2D at 0x2980773db80>,
 <matplotlib.lines.Line2D at 0x2980773dca0>,
 <matplotlib.lines.Line2D at 0x2980773ddc0>,
 <matplotlib.lines.Line2D at 0x2980773dee0>,
 <matplotlib.lines.Line2D at 0x29807758040>]
```



👇 checking the available number of classes

In [10]:
```
data['label'].value_counts()
```

Out[10]:
```
rice           100
maize          100
jute           100
cotton         100
coconut        100
papaya         100
orange         100
apple          100
muskmelon      100
watermelon     100
grapes         100
mango          100
banana         100
pomegranate    100
lentil         100
blackgram      100
mungbean       100
mothbeans      100
pigeonpeas     100
kidneybeans    100
chickpea       100
coffee         100
Name: label, dtype: int64
```

Data Reduction

Column level and row level both are used here

1. Column Level Reduction (Dimention reduction)

👇 here we are reducing the number of columns (features)

In [11]:
```
data=data.drop(['N','P','K','ph'],axis=1)
```

In [12]:
```
data.columns
```

Out[12]:
```
Index(['temperature', 'humidity', 'rainfall', 'label'], dtype='object')
```

In [13]:
```
data
```

Out[13]:

	temperature	humidity	rainfall	label
0	20.879744	82.002744	202.935536	rice
1	21.770462	80.319644	226.655537	rice
2	23.004459	82.320763	263.964248	rice
3	26.491096	80.158363	242.864034	rice
4	20.130175	81.604873	262.717340	rice
...	...	...	...	...
2195	26.774637	66.413269	177.774507	coffee
2196	27.417112	56.636362	127.924610	coffee
2197	24.131797	67.225123	173.322839	coffee
2198	26.272418	52.127394	127.175293	coffee
2199	23.603016	60.396475	140.937041	coffee

2200 rows × 4 columns

2. Row lavel Reduction (Data reduction)

👇 here we are reducing number of rows

In [14]:
```python
classes_list=["rice", "maize", "cotton", "coconut",  "orange", "apple", "watermelon","jute", "mango","coffee"]
def get_class_number(class_name):
    if class_name=='rice':
        return 0
    if class_name=='maize':
        return 1
    if class_name=='cotton':
        return 2
    if class_name=='coconut':
        return 3
    if class_name=='orange':
        return 4
    if class_name=='apple':
        return 5
    if class_name=='jute':
        return 6
    if class_name=='mango':
        return 7
    if class_name=='watermelon':
        return 8
    if class_name=='coffee':
        return 9
```

In [15]:
```python
Analysis_data=data[data['label']=='rice']
for i in range(1,len(classes_list)):
    Analysis_data=pandas.concat([Analysis_data,data[data['label']==classes_list[i]]])
data=Analysis_data
```

👇 Tranformed Data

In [16]:
```python
data
```

Out[16]:

	temperature	humidity	rainfall	label
0	20.879744	82.002744	202.935536	rice
1	21.770462	80.319644	226.655537	rice
2	23.004459	82.320763	263.964248	rice
3	26.491096	80.158363	242.864034	rice
4	20.130175	81.604873	262.717340	rice
...	...	...	...	...
2195	26.774637	66.413269	177.774507	coffee
2196	27.417112	56.636362	127.924610	coffee
2197	24.131797	67.225123	173.322839	coffee
2198	26.272418	52.127394	127.175293	coffee
2199	23.603016	60.396475	140.937041	coffee

1000 rows × 4 columns

In [17]:
```python
data['label'].value_counts()
```

Out[17]:
```
rice          100
maize         100
cotton        100
coconut       100
orange        100
apple         100
watermelon    100
jute          100
mango         100
coffee        100
Name: label, dtype: int64
```

Data Visualization 👇

In [18]:
```python
data['class_number']=data['label'].apply(get_class_number)
```

In [19]:
```
data
```

Out[19]:

	temperature	humidity	rainfall	label	class_number
0	20.879744	82.002744	202.935536	rice	0
1	21.770462	80.319644	226.655537	rice	0
2	23.004459	82.320763	263.964248	rice	0
3	26.491096	80.158363	242.864034	rice	0
4	20.130175	81.604873	262.717340	rice	0
...	...	...	...	...	...
2195	26.774637	66.413269	177.774507	coffee	9
2196	27.417112	56.636362	127.924610	coffee	9
2197	24.131797	67.225123	173.322839	coffee	9
2198	26.272418	52.127394	127.175293	coffee	9
2199	23.603016	60.396475	140.937041	coffee	9

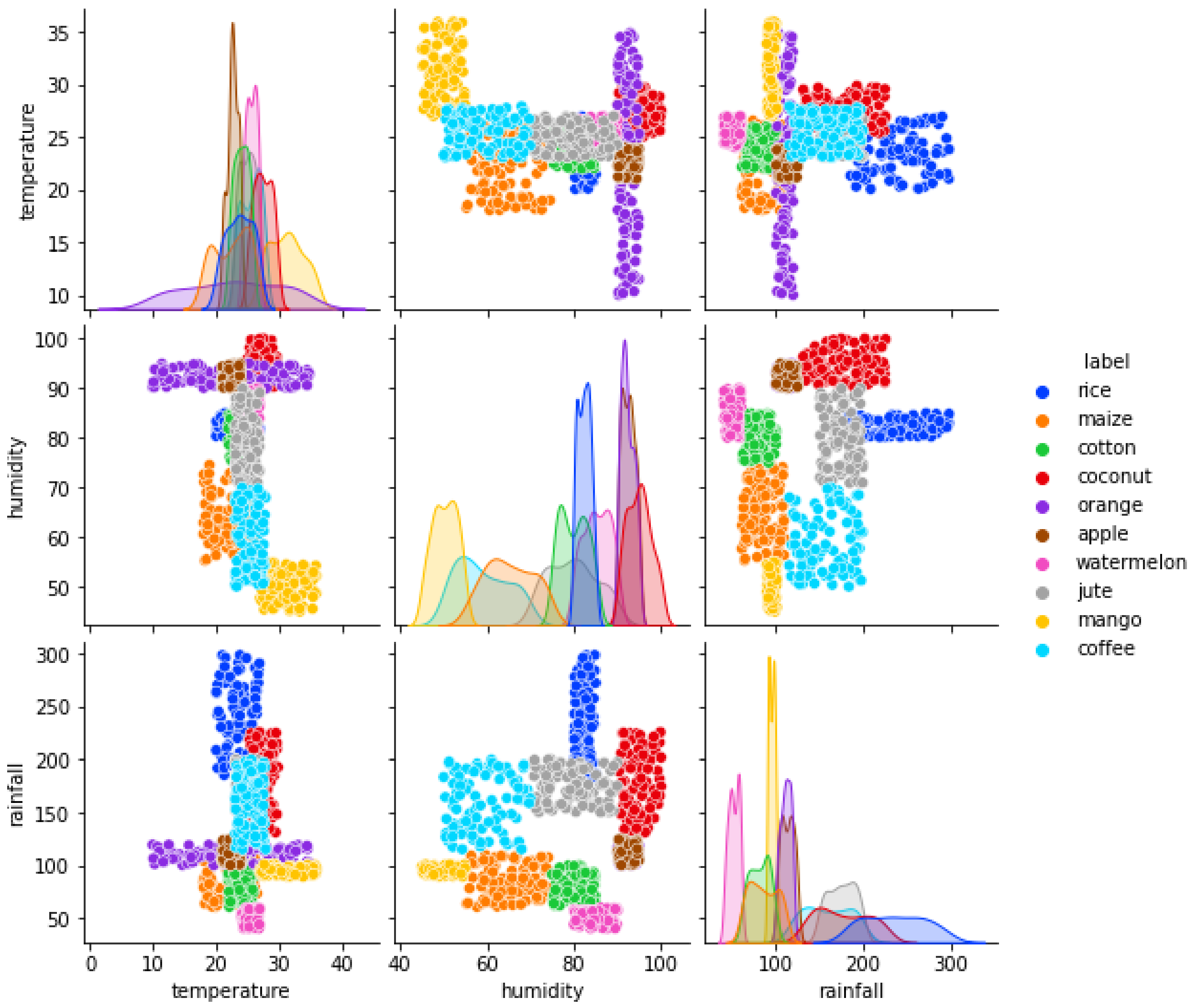
1000 rows × 5 columns

Attribute comparison paring graph

here each graph is drawn by one to one manner

In [20]:
```
seaborn.pairplot(data.iloc[:,:4], hue="label",palette="bright")
```

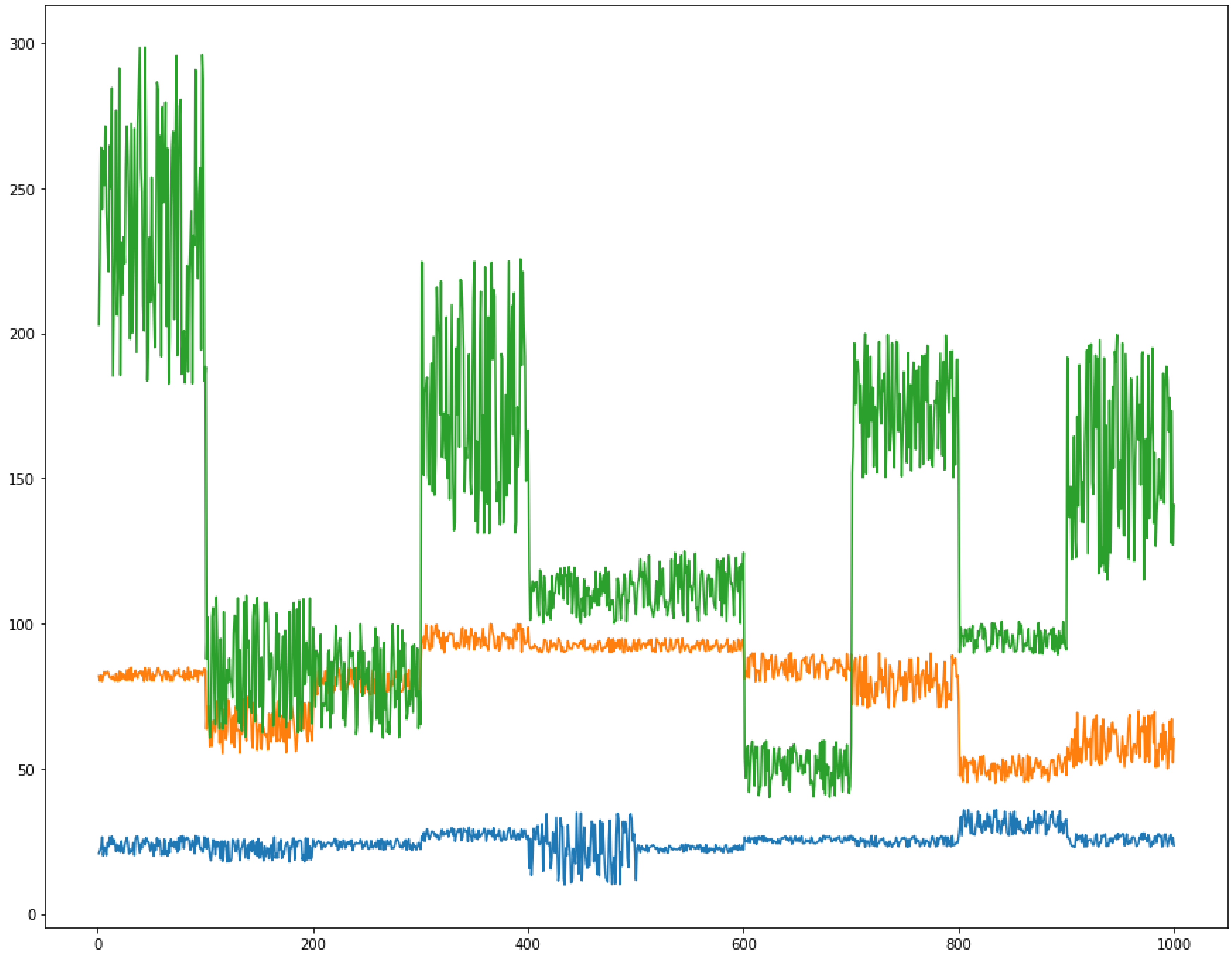
Out[20]: <seaborn.axisgrid.PairGrid at 0x29807bfed60>



Plot of data point values

In [21]:
```
pyplot.plot([i for i in range(1,len(data)+1)],data[['temperature','humidity','rainfall']])
```

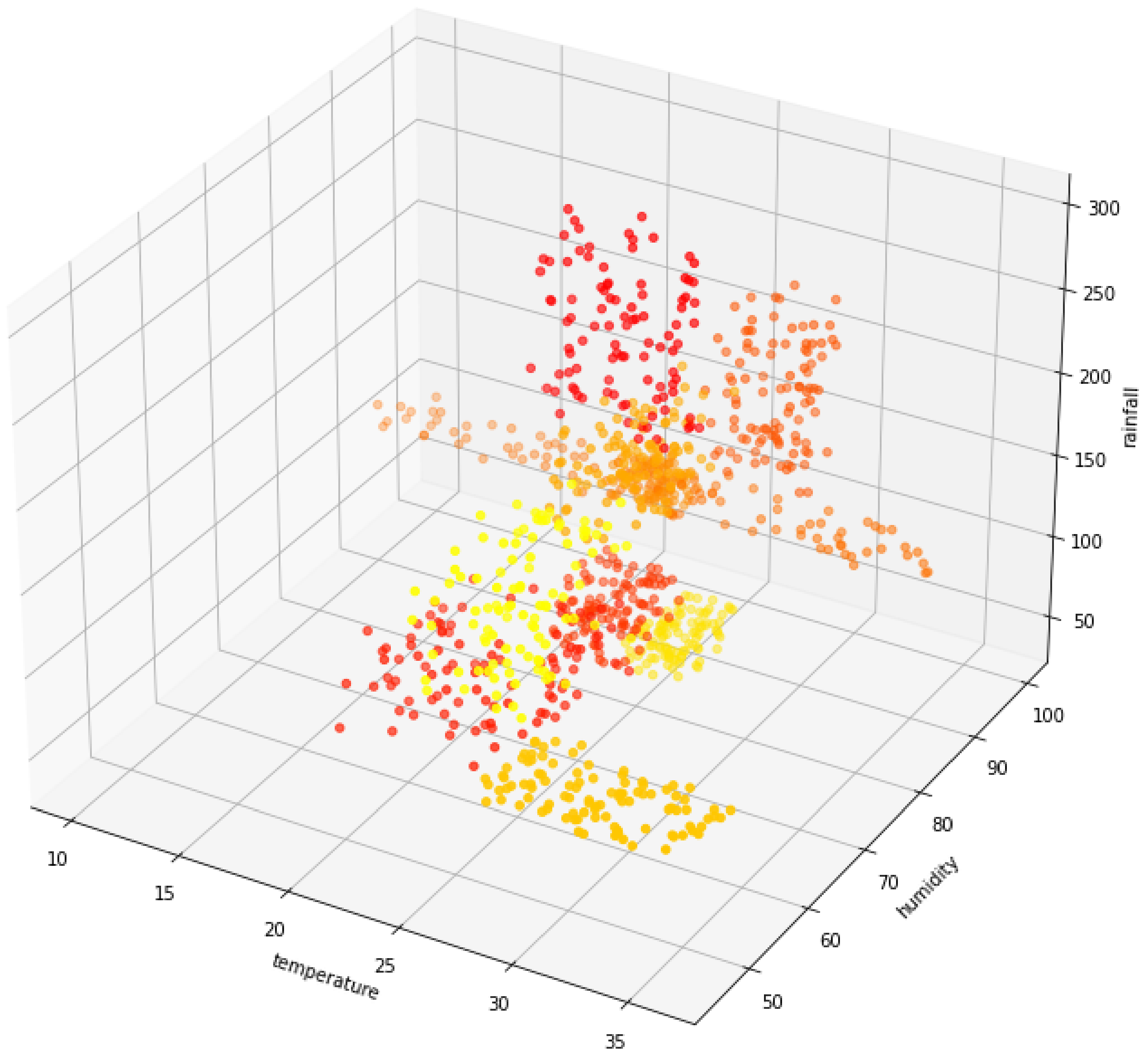
Out[21]:
```
[<matplotlib.lines.Line2D at 0x2980a384910>,
 <matplotlib.lines.Line2D at 0x2980a384940>,
 <matplotlib.lines.Line2D at 0x2980a384a90>]
```



👇 3D plot of given data points

In [22]:
```
plotter = pyplot.subplot(projection='3d')
plotter.scatter3D(data.to_numpy()[:,0], data.to_numpy()[:, 1] ,data.to_numpy()[:, 2],c=data['class_number'], cmap='autum
plotter.set_xlabel('temperature')
plotter.set_ylabel('humidity')
plotter.set_zlabel('rainfall')
```

Out[22]:
```
Text(0.5, 0, 'rainfall')
```



Data Preparation

Suffling the data set 👇

this is to get splitted data, that have all type of the classes in training and testing

In [23]:
```
shuffled_Data=data.sample(frac=1)
```

Splitting the dataset into training and testing 👇

For Training 85% data is being used and for testing 15% data is used from the given data

means 850 rows will be used for training and 150 rows will be used for testing

In [24]:
```python
Training_Data = shuffled_Data[:850]
Testing_Data = shuffled_Data[850:]
```

In [25]:
```python
Training_Data['label'].value_counts()
```

Out[25]:
```
maize         90
coffee        89
watermelon    88
coconut       86
orange        84
cotton        84
apple         84
jute          83
rice          82
mango         80
Name: label, dtype: int64
```

In [26]:
```python
Training_Data
```

Out[26]:

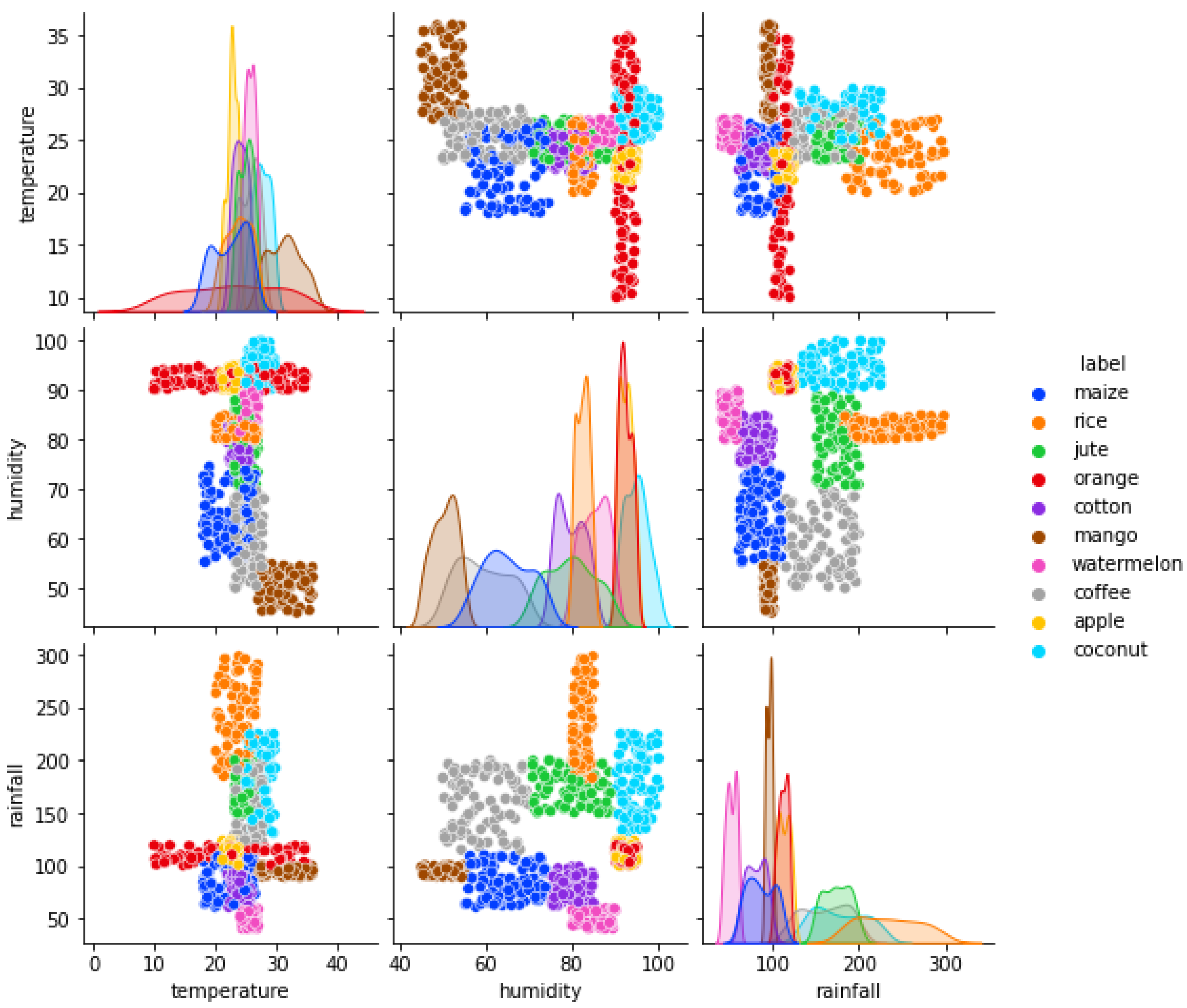
	temperature	humidity	rainfall	label	class_number
139	18.980273	74.526008	94.262494	maize	1
121	18.147101	71.094453	88.077537	maize	1
103	19.972160	57.682729	60.651715	maize	1
81	25.429775	82.946826	195.357454	rice	0
2035	25.124177	85.725306	159.571809	jute	6
...	...	...	...	...	...
1572	21.198522	92.155951	105.855435	apple	5
1583	23.761218	93.661643	100.825956	apple	5
1803	25.028872	91.537209	179.824894	coconut	3
1699	11.698946	93.256389	103.200599	orange	4
44	26.313555	82.366990	265.535594	rice	0

850 rows × 5 columns

👇 Visualizing Training Data

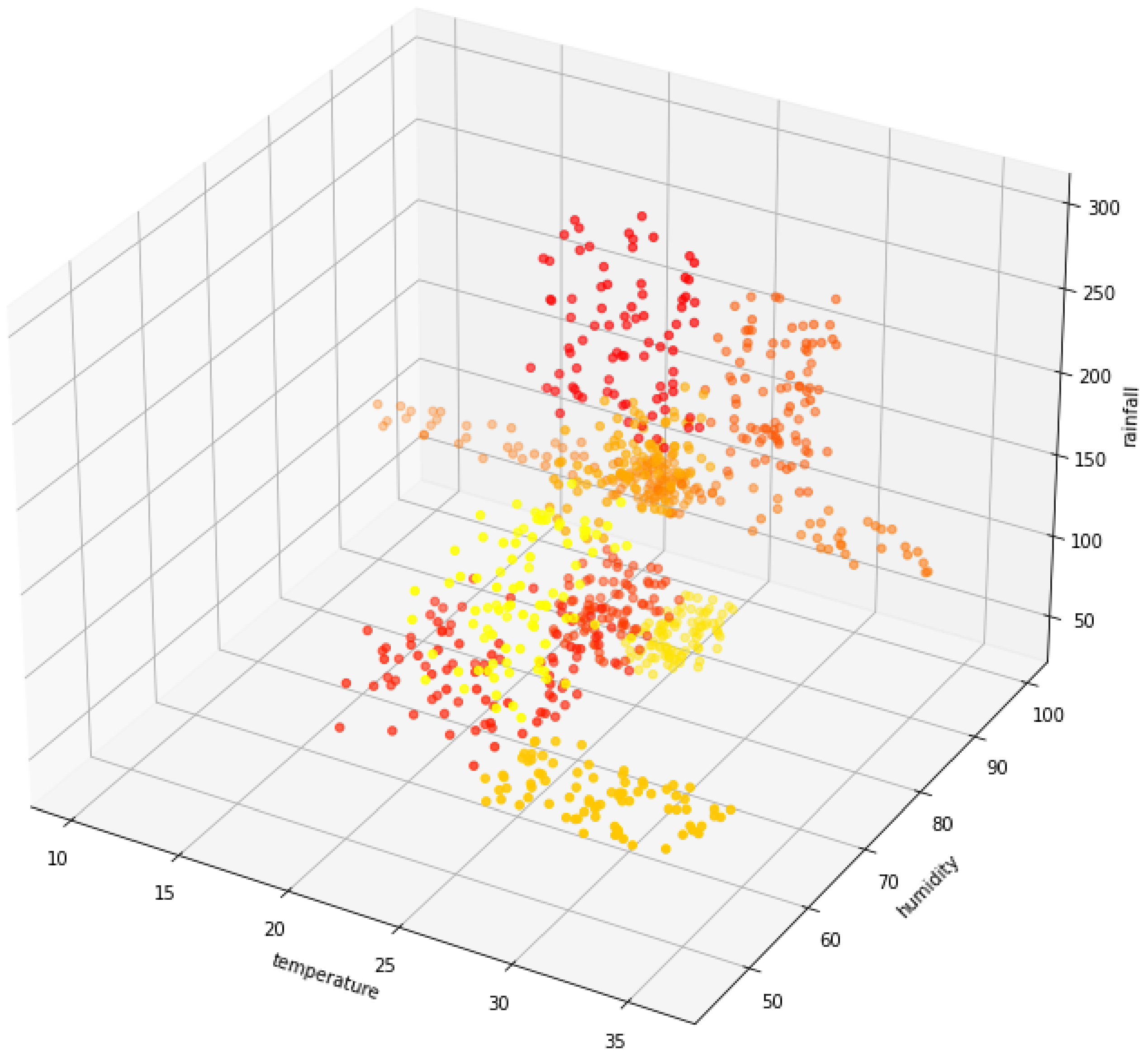
In [27]:
```python
seaborn.pairplot(Training_Data.iloc[:,:4], hue="label",palette="bright")
```

Out[27]: <seaborn.axisgrid.PairGrid at 0x2980a291f70>



In [28]:
```
plotter = pyplot.subplot(projection='3d')
plotter.scatter3D(Training_Data.to_numpy()[:,0], Training_Data.to_numpy()[:, 1] ,Training_Data.to_numpy()[:, 2],c=Trainii
plotter.set_xlabel('temperature')
plotter.set_ylabel('humidity')
plotter.set_zlabel('rainfall')
```

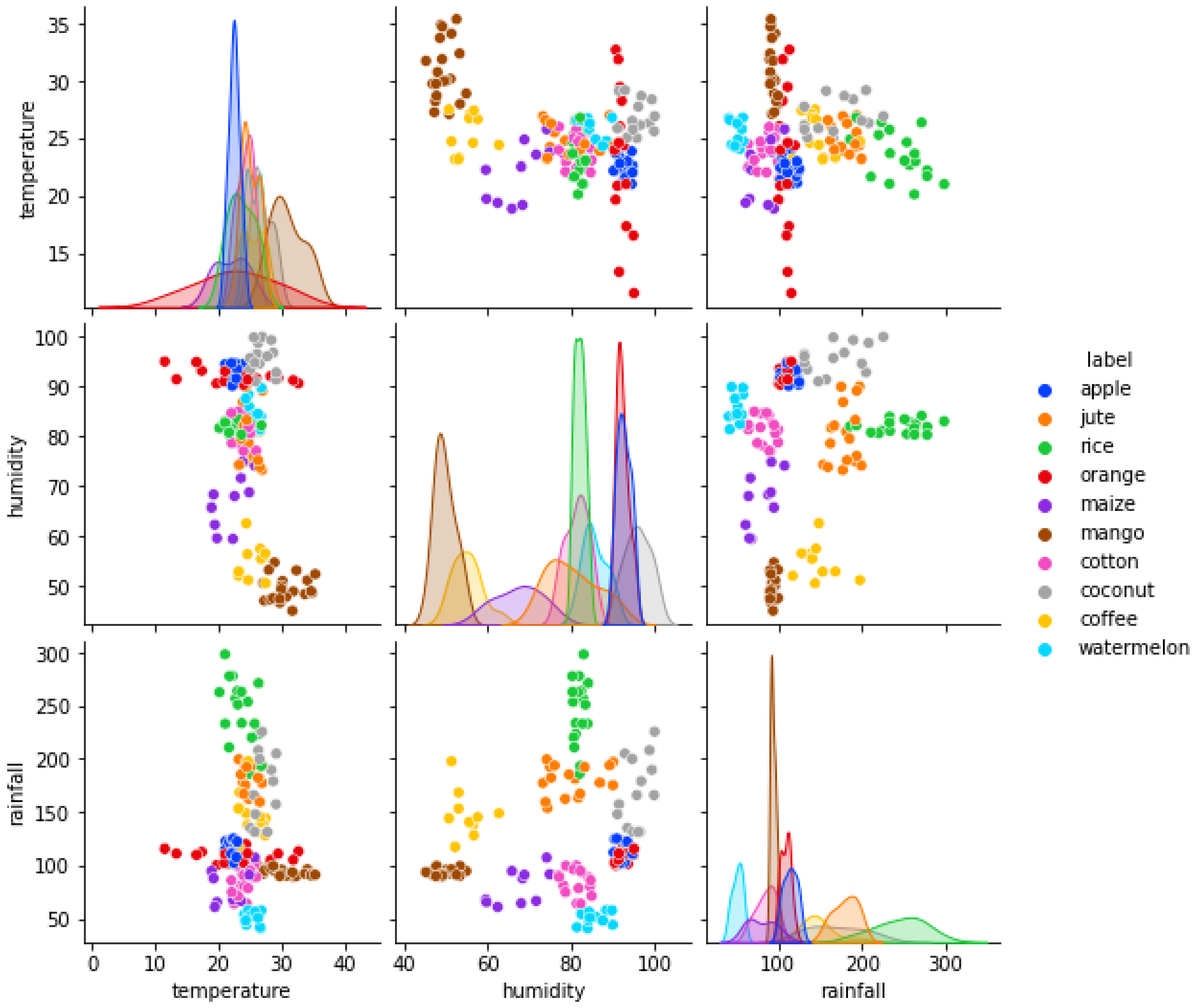
Out[28]: Text(0.5, 0, 'rainfall')



Visualizing Testing Data

In [29]:
```
seaborn.pairplot(Testing_Data.iloc[:,:4], hue="label",palette="bright")
```

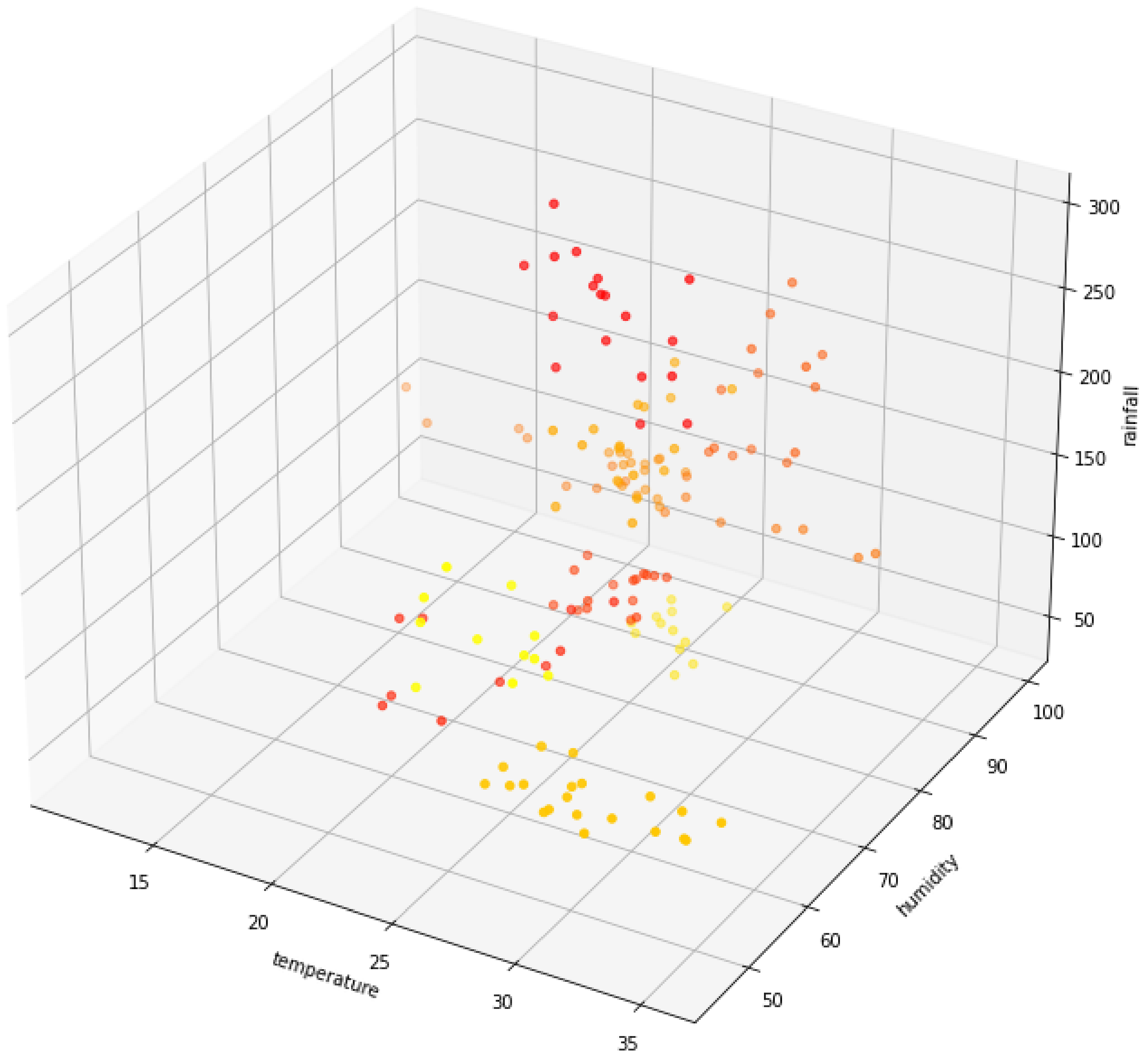
Out[29]: <seaborn.axisgrid.PairGrid at 0x2980c01faf0>



In [30]:
```
plotter = pyplot.subplot(projection='3d')
plotter.scatter3D(Testing_Data.to_numpy()[:,0], Testing_Data.to_numpy()[:, 1] ,Testing_Data.to_numpy()[:, 2],c=Testing_Da
plotter.set_xlabel('temperature')
plotter.set_ylabel('humidity')

plotter.set_zlabel('rainfall')
```

Out[30]: Text(0.5, 0, 'rainfall')



Dividing the training data features and labels 👇

this will be used for training of SVM model

In [31]:
```
training_Labels=Training_Data['label']
training_class_numbers=Training_Data['class_number']
training_Features=Training_Data.drop(['label','class_number'],axis=1)
```

In [32]:
```
training_Features.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 850 entries, 139 to 44
Data columns (total 3 columns):
 #   Column       Non-Null Count  Dtype  
---  ------       --------------  -----  
 0   temperature  850 non-null    float64
 1   humidity     850 non-null    float64
 2   rainfall     850 non-null    float64
dtypes: float64(3)
memory usage: 26.6 KB
```

In [33]:
```
training_Labels.value_counts()
```

Out[33]:
```
maize         90
coffee        89
watermelon    88
coconut       86
orange        84
cotton        84
apple         84
jute          83
rice          82
mango         80
Name: label, dtype: int64
```

dividing the testing data features and labels 👇

this will be used for testing the SVM model

In [34]:
```
testing_Labels=Testing_Data['label']
testing_class_numbers=Testing_Data['class_number']
testing_Features=Testing_Data.drop(['label','class_number'],axis=1)
```

In [35]:
```
testing_Features.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 150 entries, 1570 to 1863
Data columns (total 3 columns):
 #   Column       Non-Null Count  Dtype  
---  ------       --------------  -----  
 0   temperature  150 non-null    float64
 1   humidity     150 non-null    float64
 2   rainfall     150 non-null    float64
dtypes: float64(3)
memory usage: 4.7 KB
```

In [36]:
```
testing_Labels.value_counts()
```

Out[36]:
```
mango         20
rice          18
jute          17
apple         16
orange        16
cotton        16
coconut       14
watermelon    12
coffee        11
maize         10
Name: label, dtype: int64
```

Creating the SVM model instance(object) 👇

In [37]:
```
model=svm.SVC(kernel='linear') # 👆 this givs highest accuracy
# model=svm.SVC(kernel='poly')
# model=svm.SVC(kernel='rbf') # 👆 this was default kernal if we not give any kernal value


# 👇 give low accuracy
# model=svm.SVC(kernel='sigmoid')
```

fitting the model 👇

In [38]:
```
model.fit(training_Features,training_Labels)
```

Out[38]:
```
SVC(kernel='linear')
```

👇Printing the support vectors values

In [39]:
```
model.support_vectors_
```

Out[39]:
```
array([[ 23.80593812,  92.48879468, 119.6335548 ],
       [ 21.22503442,  90.09877774, 113.9760462 ],
       [ 21.11478672,  90.31528693, 104.5086618 ],
       [ 22.71271308,  90.45261746, 109.8852597 ],
       [ 22.13450646,  94.67695747, 112.9203223 ],
       [ 21.91191314,  91.68748063, 117.0761277 ],
       [ 21.41363812,  92.99124545, 118.3979065 ],
       [ 22.49095104,  91.70292746, 124.3915101 ],
       [ 22.45696744,  94.76285385, 114.8407725 ],
       [ 21.19909519,  90.80819418, 103.6838922 ],
       [ 22.76643029,  92.12438519, 120.4359949 ],
       [ 22.43324518,  92.48667725, 119.1025189 ],
       [ 21.18667419,  91.13435689, 122.233323  ],
       [ 21.17089176,  90.23730166, 123.6495149 ],
       [ 23.71475278,  91.53331177, 121.8961665 ],
       [ 23.64142354,  93.74461474, 116.6912176 ],
       [ 22.69780133,  92.82223419, 105.0508234 ],
       [ 23.8812458 ,  93.45067555, 104.9116663 ],
       [ 22.35628673,  91.92360477, 107.7697413 ],
```

👇 this is the number of the support vectors generated for respective class

In [40]:
```
model.n_support_
```

Out[40]:
```
array([80,  5,  5,  7, 24, 11,  6, 82, 18,  3])
```

In [41]:
```
len(model.support_vectors_)
```

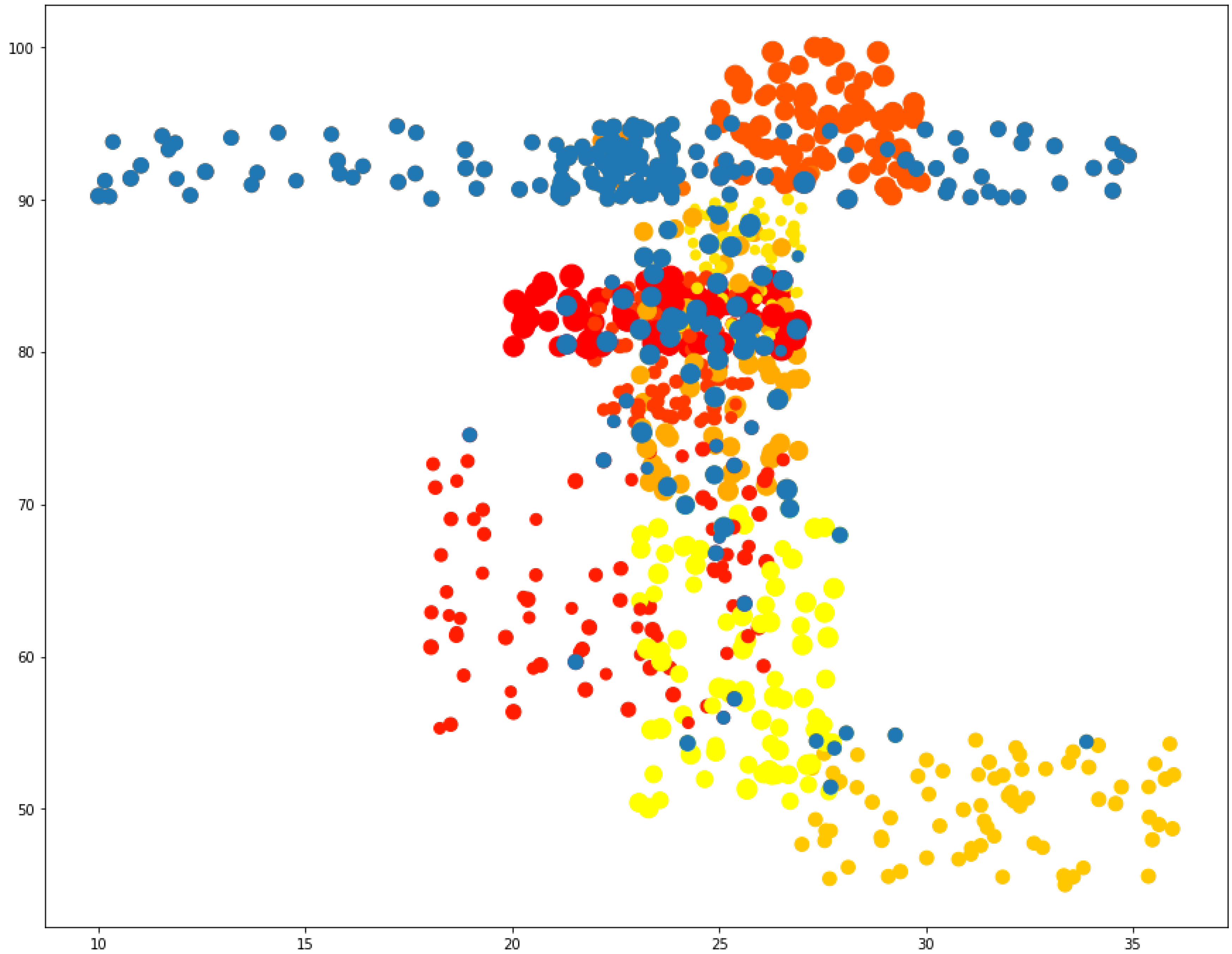
Out[41]:
```
241
```

Visualization of Support Vectors 👇

👇 2D plot

In [42]:
```
pyplot.scatter(training_Features.to_numpy()[:, 0],training_Features.to_numpy()[:, 1],training_Features.to_numpy()[:, 2],
pyplot.scatter(model.support_vectors_[:,0],model.support_vectors_[:,1],model.support_vectors_[:,2])
```

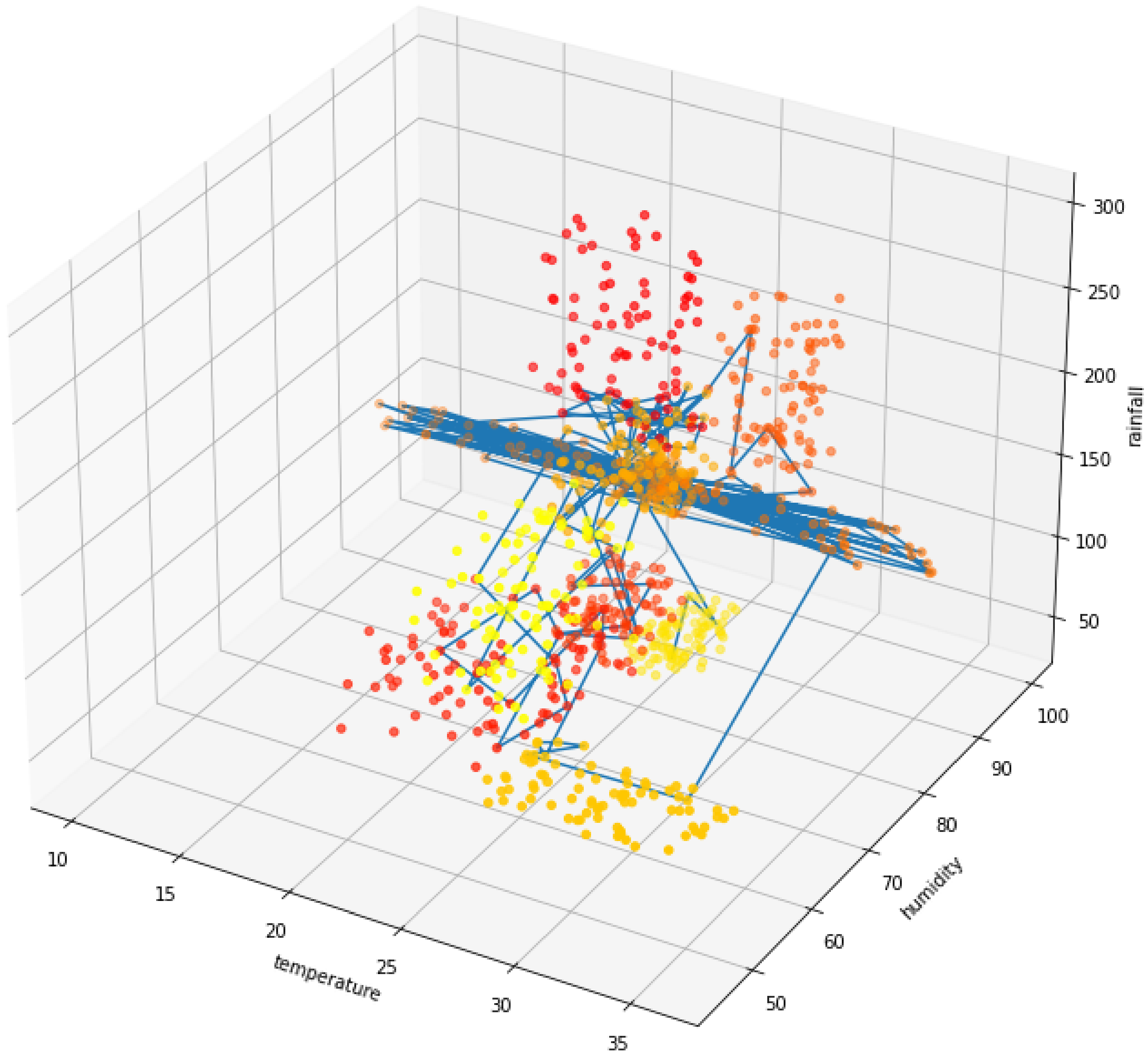
Out[42]:
```
<matplotlib.collections.PathCollection at 0x2980c9b8790>
```



👇 3D plot

In [43]:
```python
plotter = pyplot.subplot(projection='3d')
plotter.scatter3D(training_Features.to_numpy()[:, 0], training_Features.to_numpy()[:, 1] ,training_Features.to_numpy()[:
plotter.plot3D(model.support_vectors_[:,0],model.support_vectors_[:,1],model.support_vectors_[:,2])
plotter.set_xlabel('temperature')
plotter.set_ylabel('humidity')
plotter.set_zlabel('rainfall')
```

Out[43]: Text(0.5, 0, 'rainfall')



👆 Blue colored lines are Support Vectors

others are Datapoints

Now model is Trained 👆

Optional Part 👇

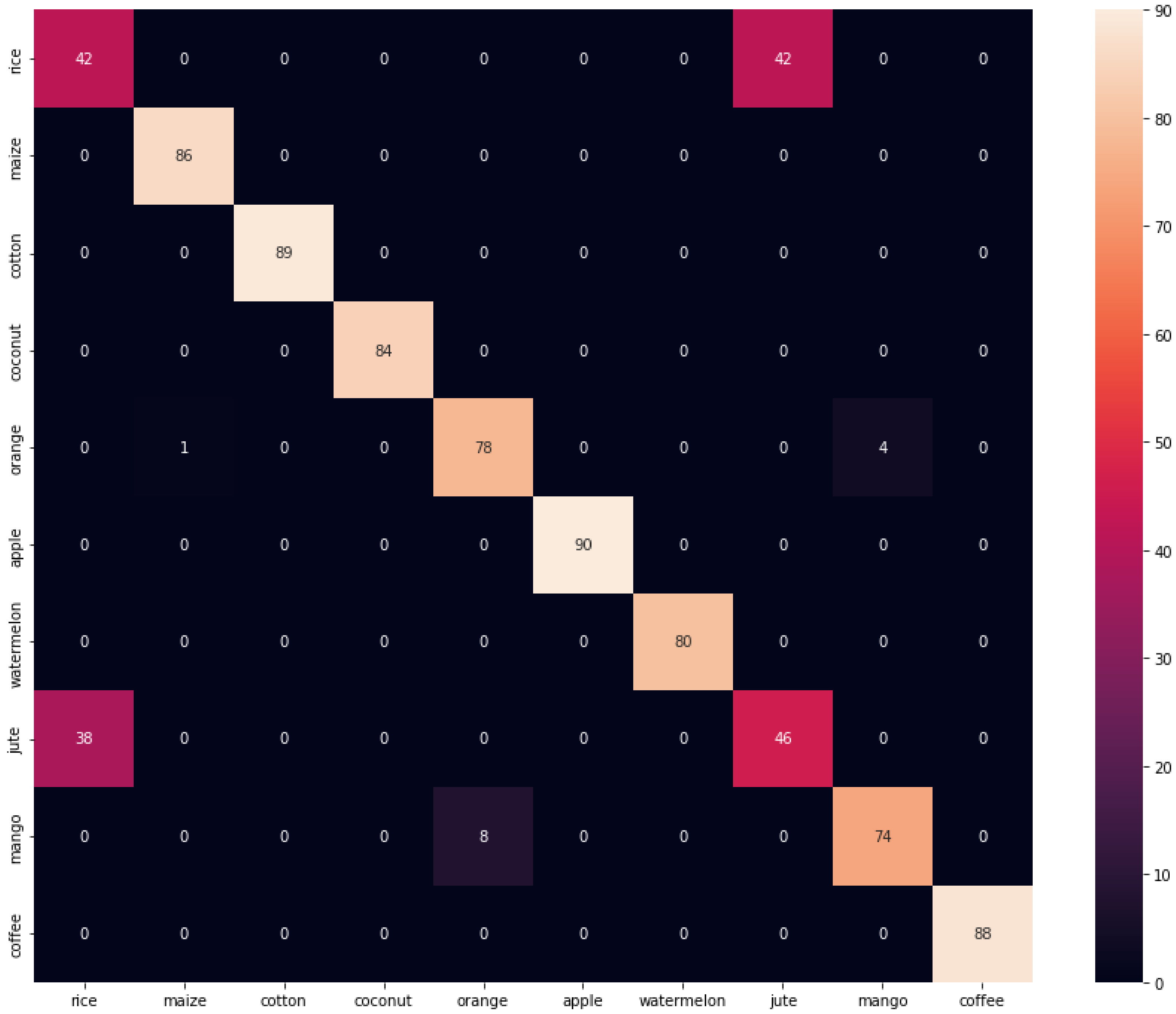
checking model on training data to check training accuracy (not needed)

In [44]:
```
training_predicted_values=model.predict(training_Features)
training_classification_data=confusion_matrix(training_Labels,training_predicted_values)
seaborn.heatmap(training_classification_data,annot=True,xticklabels=classes_list,yticklabels=classes_list)
print(classification_report(training_Labels,training_predicted_values,target_names=classes_list))
```

```
              precision    recall  f1-score   support

        rice       0.53      0.50      0.51        84
       maize       0.99      1.00      0.99        86
      cotton       1.00      1.00      1.00        89
     coconut       1.00      1.00      1.00        84
      orange       0.91      0.94      0.92        83
       apple       1.00      1.00      1.00        90
  watermelon       1.00      1.00      1.00        80
        jute       0.52      0.55      0.53        84
       mango       0.95      0.90      0.92        82
      coffee       1.00      1.00      1.00        88

    accuracy                           0.89       850
   macro avg       0.89      0.89      0.89       850
weighted avg       0.89      0.89      0.89       850
```



Training accuracy is 89%

Now Testing the model 👇

In [45]:
```
predicted_values=model.predict(testing_Features)
```

In [46]:
```
predicted_values
```

Out[46]:
```
array(['apple', 'jute', 'rice', 'orange', 'rice', 'maize', 'mango',
       'jute', 'cotton', 'mango', 'cotton', 'mango', 'coconut', 'apple',
       'orange', 'cotton', 'orange', 'mango', 'mango', 'coconut',
       'orange', 'apple', 'mango', 'coffee', 'mango', 'orange', 'cotton',
       'apple', 'orange', 'maize', 'cotton', 'rice', 'orange', 'orange',
       'rice', 'watermelon', 'rice', 'coconut', 'watermelon', 'coffee',
       'watermelon', 'maize', 'watermelon', 'jute', 'apple', 'coffee',
       'orange', 'mango', 'cotton', 'coffee', 'coconut', 'rice', 'mango',
       'jute', 'cotton', 'jute', 'jute', 'apple', 'rice', 'apple',
       'mango', 'coconut', 'rice', 'orange', 'cotton', 'jute', 'coconut',
       'rice', 'apple', 'jute', 'rice', 'mango', 'jute', 'apple',
       'cotton', 'cotton', 'watermelon', 'coconut', 'coconut', 'coconut',
       'maize', 'orange', 'orange', 'apple', 'mango', 'watermelon',
       'watermelon', 'coconut', 'jute', 'jute', 'maize', 'mango', 'mango',
       'cotton', 'apple', 'watermelon', 'coffee', 'coffee', 'rice',
       'watermelon', 'coffee', 'cotton', 'orange', 'cotton', 'coconut',
       'cotton', 'watermelon', 'coffee', 'maize', 'jute', 'jute', 'mango',
       'orange', 'cotton', 'jute', 'apple', 'rice', 'rice', 'maize',
       'coconut', 'coconut', 'jute', 'mango', 'cotton', 'maize', 'orange',
```

Following will show that what is actual value and what is predicted by model 👇

In [47]:
```
predicted_values=list(predicted_values)
testing_Labels=list(testing_Labels)
print("Actual Values --> Predicted values")
for i in range(len(predicted_values)):
    print("      ",testing_Labels[i]," --> ",predicted_values[i])
```

```
      watermelon  -->  watermelon
      coffee  -->  coffee
      jute  -->  rice
      maize  -->  maize
      apple  -->  apple
      jute  -->  jute
      rice  -->  rice
      cotton  -->  cotton

      rice  -->  rice
      orange  -->  apple
      apple  -->  orange
      mango  -->  mango
      coffee  -->  coffee
      coffee  -->  coffee
      watermelon  -->  watermelon
      mango  -->  mango
      mango  -->  mango
      orange  -->  orange
      orange  -->  orange
```

plotting the confusion matrix for model of tested data 👇

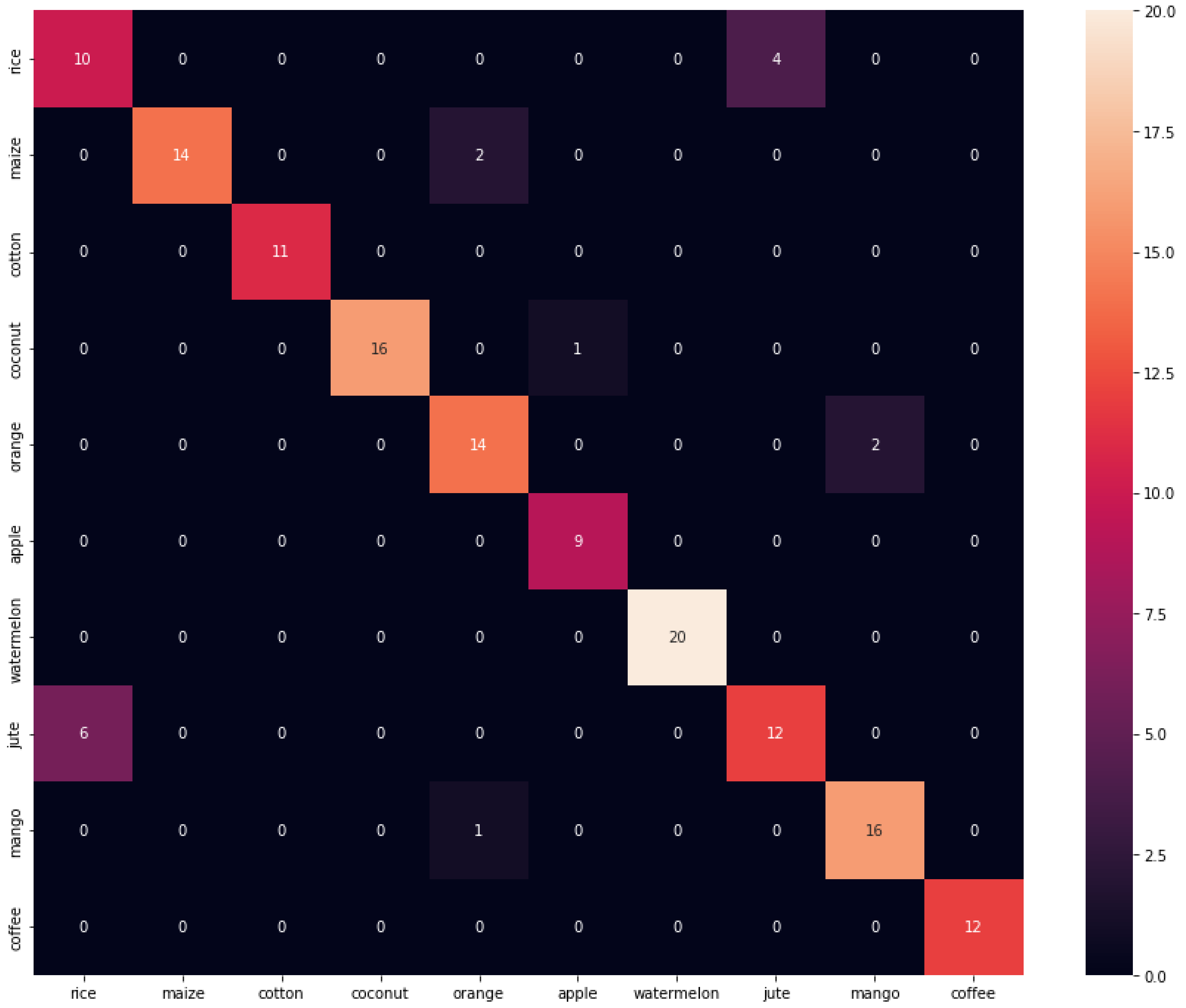
In [48]:
```
classification_data=confusion_matrix(predicted_values,testing_Labels)
```

In [49]:
```
classification_data
```

Out[49]:
```
array([[10,  0,  0,  0,  0,  0,  0,  4,  0,  0],
       [ 0, 14,  0,  0,  2,  0,  0,  0,  0,  0],
       [ 0,  0, 11,  0,  0,  0,  0,  0,  0,  0],
       [ 0,  0,  0, 16,  0,  1,  0,  0,  0,  0],
       [ 0,  0,  0,  0, 14,  0,  0,  0,  2,  0],
       [ 0,  0,  0,  0,  0,  9,  0,  0,  0,  0],
       [ 0,  0,  0,  0,  0,  0, 20,  0,  0,  0],
       [ 6,  0,  0,  0,  0,  0,  0, 12,  0,  0],
       [ 0,  0,  0,  0,  1,  0,  0,  0, 16,  0],
       [ 0,  0,  0,  0,  0,  0,  0,  0,  0, 12]], dtype=int64)
```

In [50]:
```
seaborn.heatmap(classification_data,annot=True,xticklabels=classes_list,yticklabels=classes_list)
```

Out[50]: <AxesSubplot:>



This is the calculation of accuracy of the model and precision of the respective classes 👇

In [51]:
```
print(classification_report(testing_Labels,predicted_values,target_names=classes_list))
```

```
              precision    recall  f1-score   support

        rice       0.71      0.62      0.67        16
       maize       0.88      1.00      0.93        14
      cotton       1.00      1.00      1.00        11
     coconut       0.94      1.00      0.97        16
      orange       0.88      0.82      0.85        17
       apple       1.00      0.90      0.95        10
  watermelon       1.00      1.00      1.00        20
        jute       0.67      0.75      0.71        16
       mango       0.94      0.89      0.91        18
      coffee       1.00      1.00      1.00        12

    accuracy                           0.89       150
   macro avg       0.90      0.90      0.90       150
weighted avg       0.89      0.89      0.89       150
```

Testing on new Data 👇

for,

1) temperature= 30
2) humidity=49
3) rainfall= 95

(Correct Output Should be Mango)

In [52]:
```
new_data=[30,49,95]
print(model.predict([new_data])[0])
```

```
mango
```