

In [1]:

```

1 import pandas as pd
2 import numpy as np
3 import matplotlib.pyplot as plt
4 %matplotlib inline
5 import seaborn as sns
6 from IPython import get_ipython
7 import warnings
8 warnings.filterwarnings("ignore")

```

In [2]:

```
1 data = pd.read_csv('crop.csv')
```

In [3]:

```
1 data.head()
```

Out[3]:

	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

In [4]:

```
1 data.tail()
```

Out[4]:

	N	P	K	temperature	humidity	ph	rainfall	label
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

In [5]:



```
1 data.shape
```

Out[5]:

```
(2200, 8)
```

In [6]:



```
1 data.columns
```

Out[6]:

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

In [7]:



```
1 data.duplicated().sum()
```

Out[7]:

```
0
```

In [8]:



```
1 data.isnull().sum()
```

Out[8]:

```
N          0
P          0
K          0
temperature 0
humidity    0
ph          0
rainfall    0
label       0
dtype: int64
```

In [9]:

```
1 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 [10]:

```
1 data.describe()
```

Out[10]:

	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	103.463291
std	36.917334	32.985883	50.647931	5.063749	22.263812	0.773938	54.963549
min	0.000000	5.000000	5.000000	8.825675	14.258040	3.504752	20.279000
25%	21.000000	28.000000	20.000000	22.769375	60.261953	5.971693	64.560000
50%	37.000000	51.000000	32.000000	25.598693	80.473146	6.425045	94.860000
75%	84.250000	68.000000	49.000000	28.561654	89.948771	6.923643	124.260000
max	140.000000	145.000000	205.000000	43.675493	99.981876	9.935091	298.540000

In [11]:

```
1 data.nunique()
```

Out[11]:

```
N          137
P          117
K           73
temperature 2200
humidity     2200
ph           2200
rainfall     2200
label        22
dtype: int64
```

In [12]:



```
1 data['label'].unique()
```

Out[12]:

```
array(['rice', 'maize', 'chickpea', 'kidneybeans', 'pigeonpeas',  
      'mothbeans', 'mungbean', 'blackgram', 'lentil', 'pomegranate',  
      'banana', 'mango', 'grapes', 'watermelon', 'muskmelon', 'apple',  
      'orange', 'papaya', 'coconut', 'cotton', 'jute', 'coffee'],  
      dtype=object)
```

In [13]:



```
1 data['label'].value_counts()
```

Out[13]:

```
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
```

In [14]:



```
1 crop_summary = pd.pivot_table(data, index=['label'],  
2                               aggfunc='mean')
```

In [15]:

1

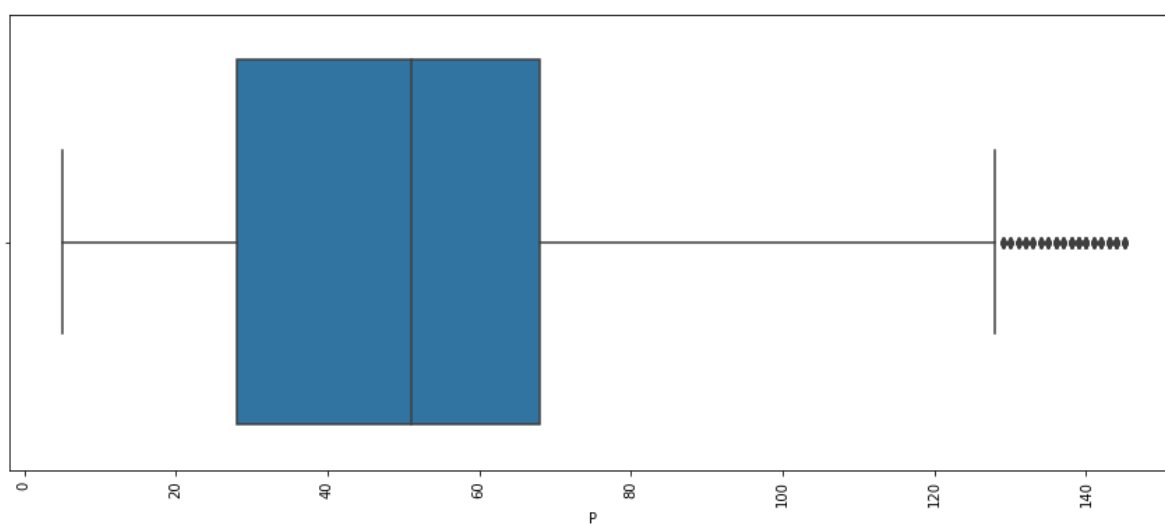
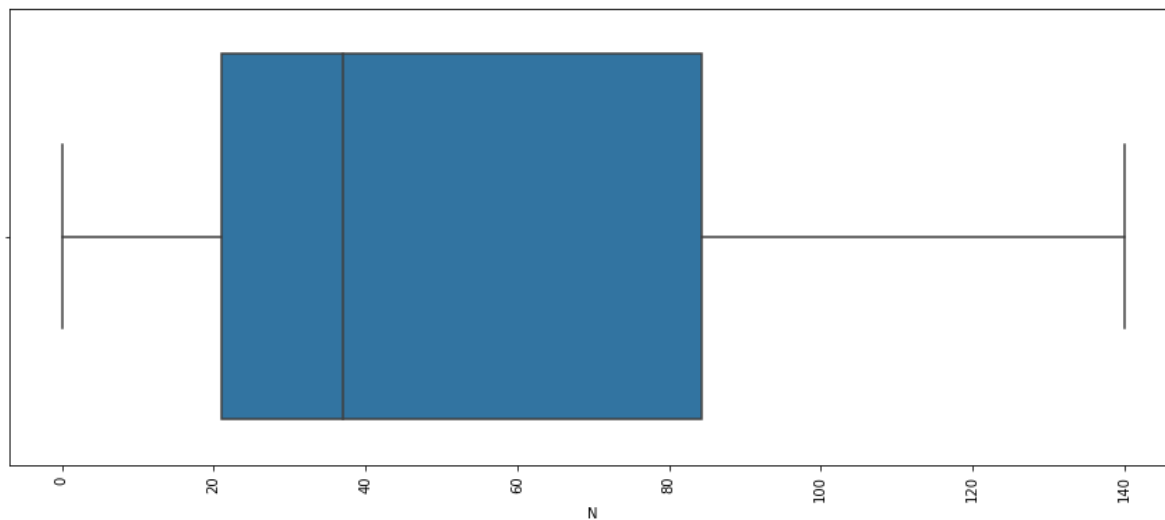
crop\_summary

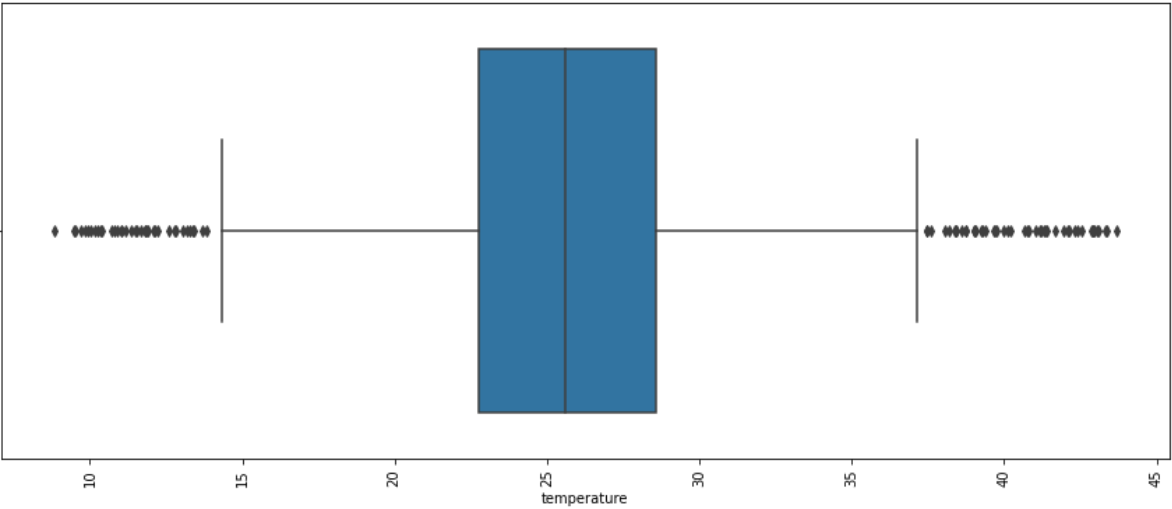
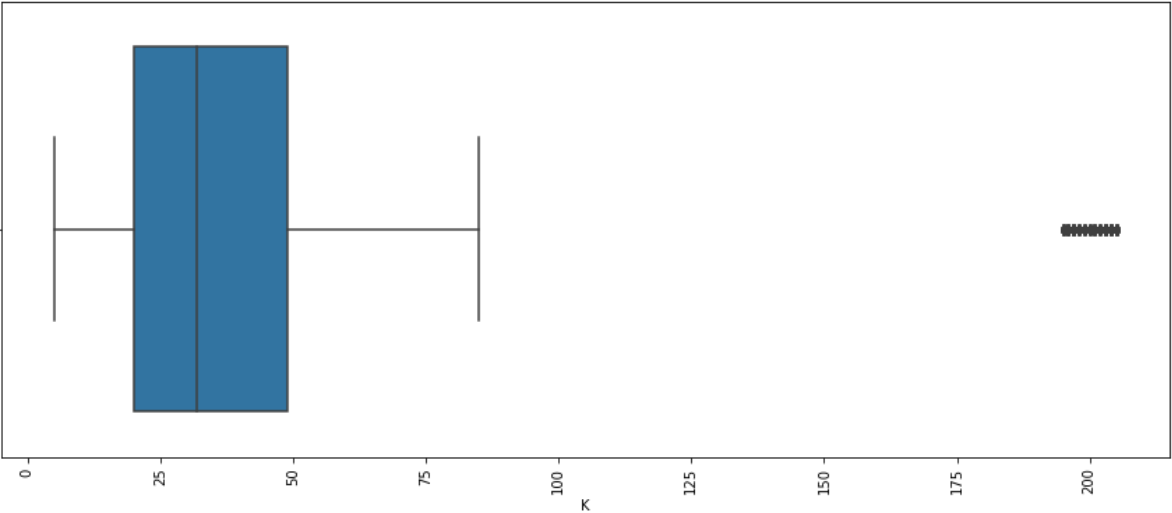
Out[15]:

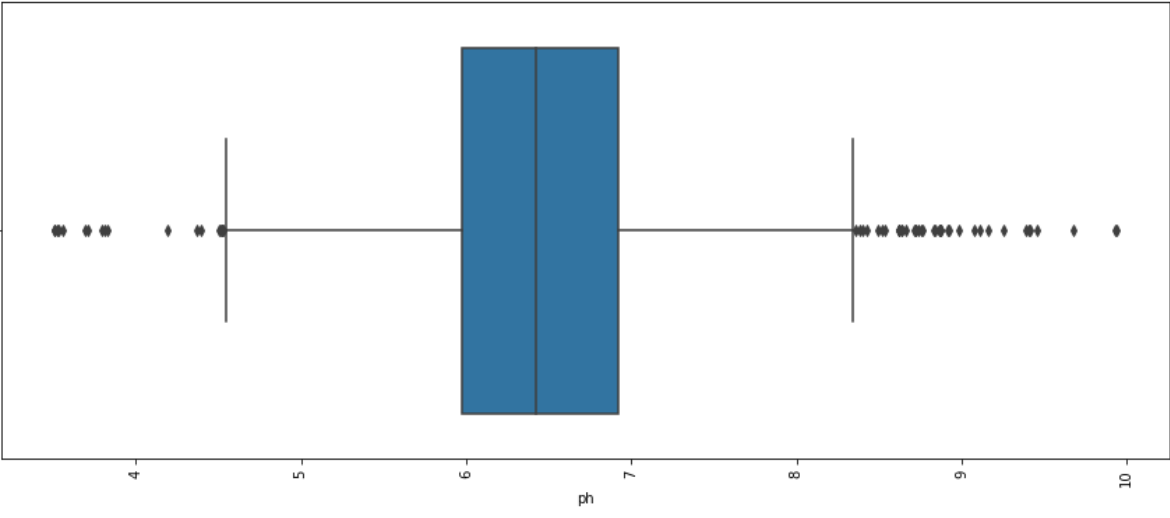
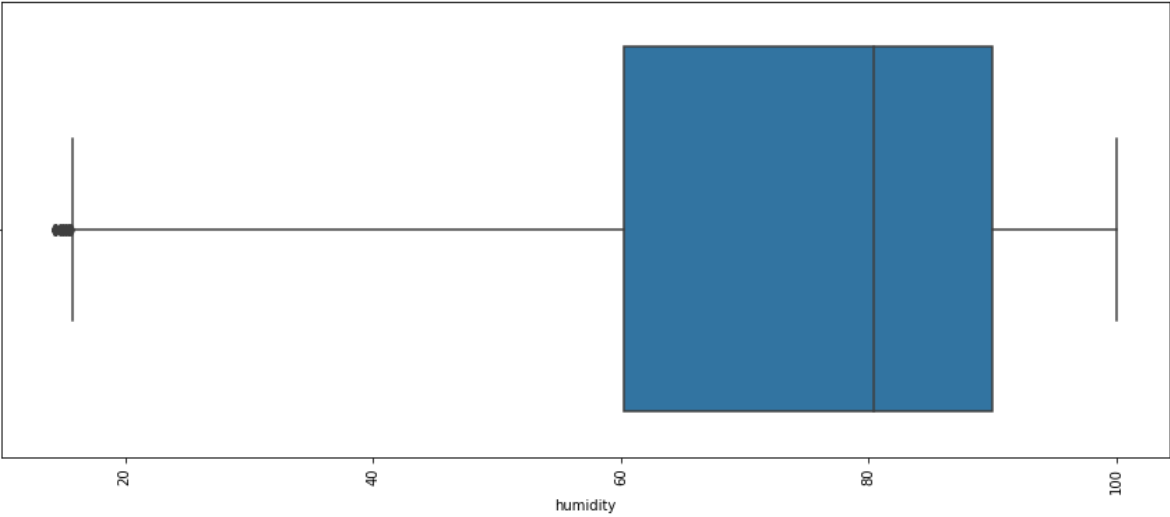
	K	N	P	humidity	ph	rainfall	temperature
label							
apple	199.89	20.80	134.22	92.333383	5.929663	112.654779	22.630942
banana	50.05	100.23	82.01	80.358123	5.983893	104.626980	27.376798
blackgram	19.24	40.02	67.47	65.118426	7.133952	67.884151	29.973340
chickpea	79.92	40.09	67.79	16.860439	7.336957	80.058977	18.872847
coconut	30.59	21.98	16.93	94.844272	5.976562	175.686646	27.409892
coffee	29.94	101.20	28.74	58.869846	6.790308	158.066295	25.540477
cotton	19.56	117.77	46.24	79.843474	6.912675	80.398043	23.988958
grapes	200.11	23.18	132.53	81.875228	6.025937	69.611829	23.849575
jute	39.99	78.40	46.86	79.639864	6.732778	174.792798	24.958376
kidneybeans	20.05	20.75	67.54	21.605357	5.749411	105.919778	20.115085
lentil	19.41	18.77	68.36	64.804785	6.927932	45.680454	24.509052
maize	19.79	77.76	48.44	65.092249	6.245190	84.766988	22.389204
mango	29.92	20.07	27.18	50.156573	5.766373	94.704515	31.208770
mothbeans	20.23	21.44	48.01	53.160418	6.831174	51.198487	28.194920
mungbean	19.87	20.99	47.28	85.499975	6.723957	48.403601	28.525775
muskmelon	50.08	100.32	17.72	92.342802	6.358805	24.689952	28.663066
orange	10.01	19.58	16.55	92.170209	7.016957	110.474969	22.765725
papaya	50.04	49.88	59.05	92.403388	6.741442	142.627839	33.723859
pigeonpeas	20.29	20.73	67.73	48.061633	5.794175	149.457564	27.741762
pomegranate	40.21	18.87	18.75	90.125504	6.429172	107.528442	21.837842
rice	39.87	79.89	47.58	82.272822	6.425471	236.181114	23.689332
watermelon	50.22	99.42	17.00	85.160375	6.495778	50.786219	25.591767

In [18]:

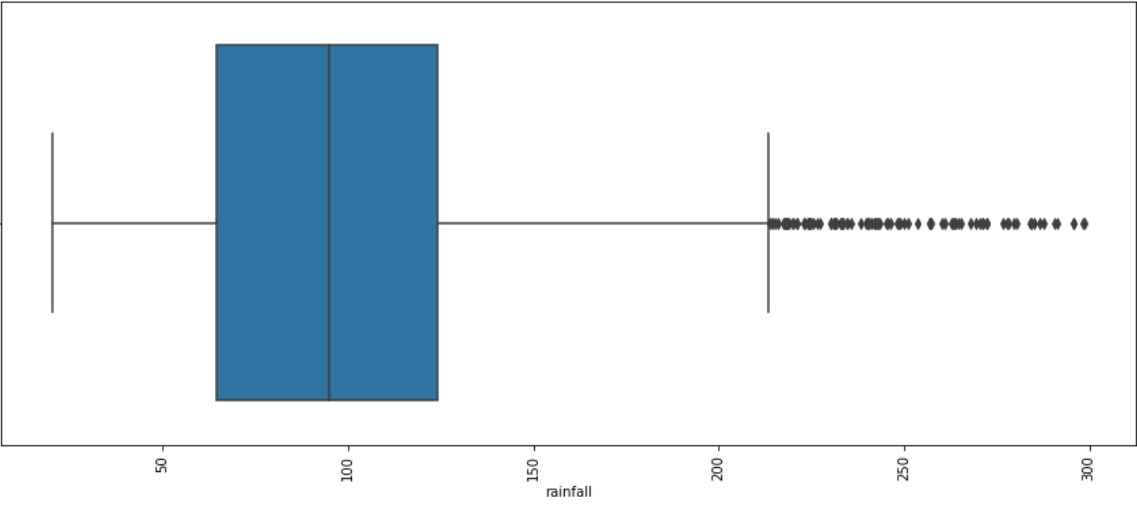
```
1 data1 = data[['N', 'P', 'K', 'temperature', 'humidity', 'ph', 'rainfall']]
2 for i in data1.columns:
3     plt.figure(figsize=(15,6))
4     sns.boxplot(data1[i])
5     plt.xticks(rotation = 90)
6     plt.show()
```











In [31]:



```
1 crop_summary_new = crop_summary.reset_index()
```

In [32]:



```
1 crop_summary_new
```

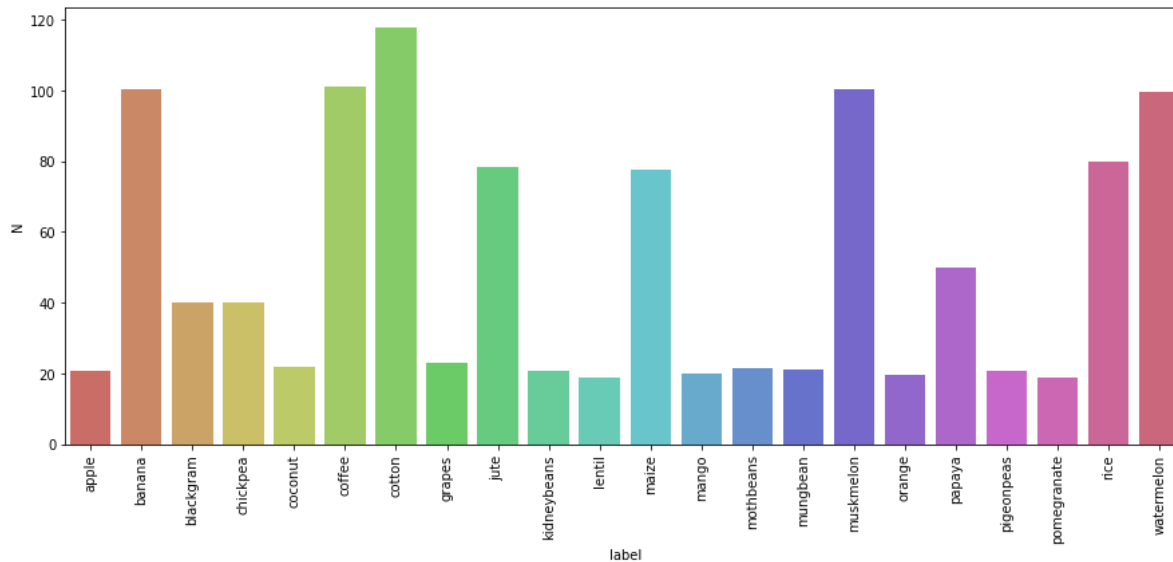
Out[32]:

	label	K	N	P	humidity	ph	rainfall	temperature
0	apple	199.89	20.80	134.22	92.333383	5.929663	112.654779	22.630942
1	banana	50.05	100.23	82.01	80.358123	5.983893	104.626980	27.376798
2	blackgram	19.24	40.02	67.47	65.118426	7.133952	67.884151	29.973340
3	chickpea	79.92	40.09	67.79	16.860439	7.336957	80.058977	18.872847
4	coconut	30.59	21.98	16.93	94.844272	5.976562	175.686646	27.409892
5	coffee	29.94	101.20	28.74	58.869846	6.790308	158.066295	25.540477
6	cotton	19.56	117.77	46.24	79.843474	6.912675	80.398043	23.988958
7	grapes	200.11	23.18	132.53	81.875228	6.025937	69.611829	23.849575
8	jute	39.99	78.40	46.86	79.639864	6.732778	174.792798	24.958376
9	kidneybeans	20.05	20.75	67.54	21.605357	5.749411	105.919778	20.115085
10	lentil	19.41	18.77	68.36	64.804785	6.927932	45.680454	24.509052
11	maize	19.79	77.76	48.44	65.092249	6.245190	84.766988	22.389204
12	mango	29.92	20.07	27.18	50.156573	5.766373	94.704515	31.208770
13	mothbeans	20.23	21.44	48.01	53.160418	6.831174	51.198487	28.194920
14	mungbean	19.87	20.99	47.28	85.499975	6.723957	48.403601	28.525775
15	muskmelon	50.08	100.32	17.72	92.342802	6.358805	24.689952	28.663066
16	orange	10.01	19.58	16.55	92.170209	7.016957	110.474969	22.765725
17	papaya	50.04	49.88	59.05	92.403388	6.741442	142.627839	33.723859
18	pigeonpeas	20.29	20.73	67.73	48.061633	5.794175	149.457564	27.741762
19	pomegranate	40.21	18.87	18.75	90.125504	6.429172	107.528442	21.837842
20	rice	39.87	79.89	47.58	82.272822	6.425471	236.181114	23.689332
21	watermelon	50.22	99.42	17.00	85.160375	6.495778	50.786219	25.591767

In [33]:



```
1 plt.figure(figsize=(15,6))
2 sns.barplot(y = 'N', x = 'label', data=crop_summary_new, palette = 'hls')
3 plt.xticks(rotation = 90)
4 plt.show()
```



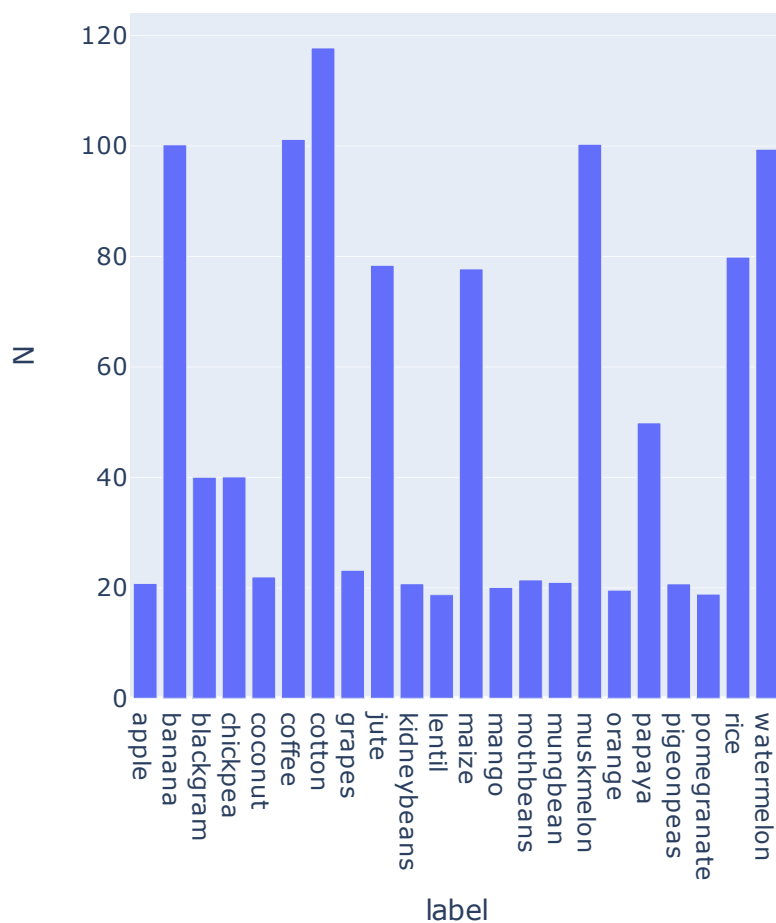
In [34]:



```
1 import plotly.graph_objects as go
2 import plotly.express as px
3 from plotly.subplots import make_subplots
```

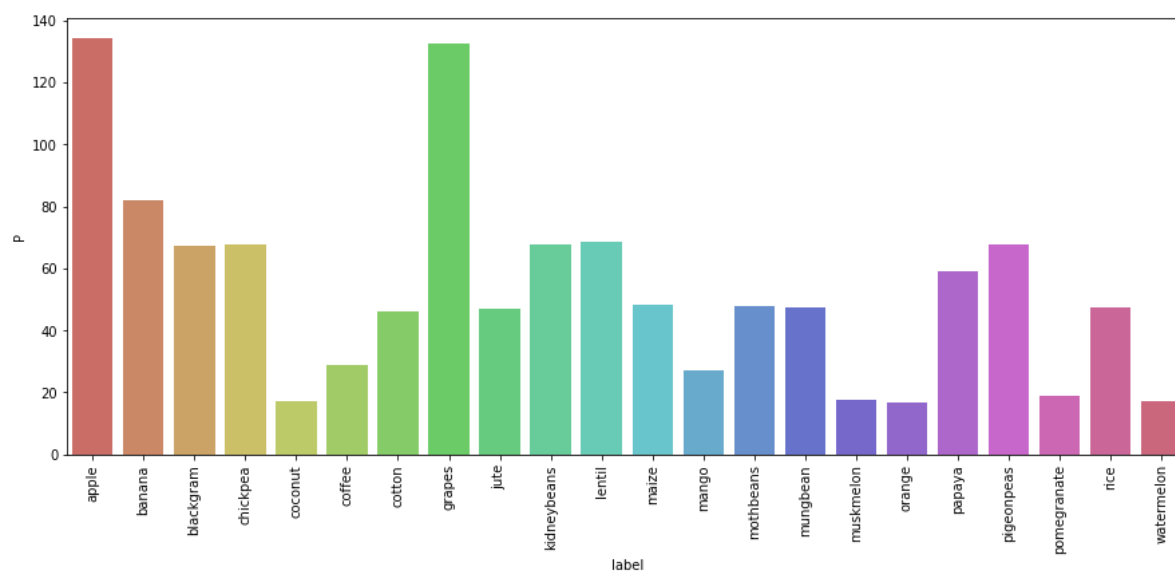
In [35]:

```
1 fig1 = px.bar(crop_summary_new, x='label', y='N')
2 fig1.show()
```



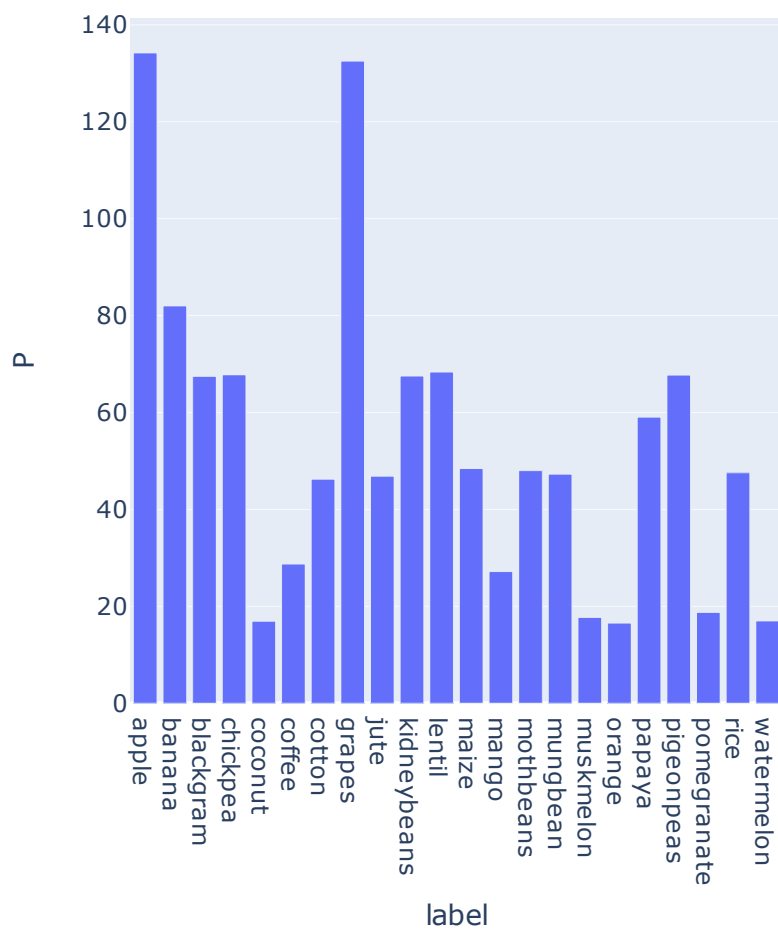
In [36]:

```
1 plt.figure(figsize=(15,6))
2 sns.barplot(y = 'P', x = 'label', data=crop_summary_new, palette = 'hls')
3 plt.xticks(rotation = 90)
4 plt.show()
```



In [37]:

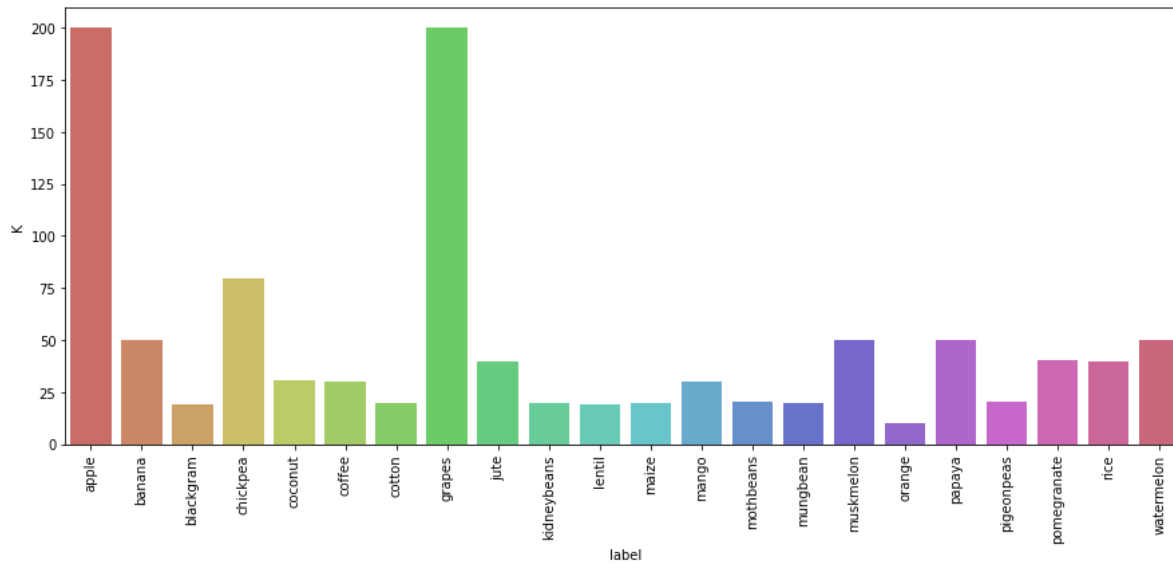
```
1 fig2 = px.bar(crop_summary_new, x='label', y='P')  
2 fig2.show()
```



In [38]:

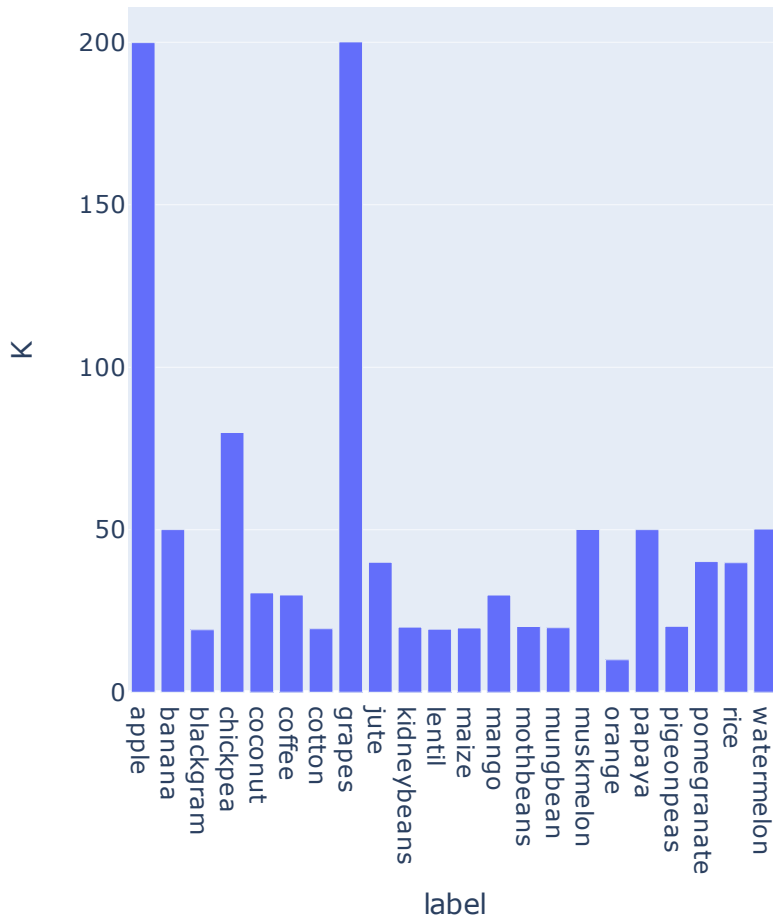


```
1 plt.figure(figsize=(15,6))
2 sns.barplot(y = 'K', x = 'label', data=crop_summary_new, palette = 'hls')
3 plt.xticks(rotation = 90)
4 plt.show()
```



In [39]:

```
1 fig3 = px.bar(crop_summary_new, x='label', y='K')
2 fig3.show()
```



In [40]:

```
1 colorarr = ['#0592D0', '#Cd7f32', '#E97451', '#Bdb76b', '#954535', '#C2b280', '#808080',
2             '#32cd32', '#39ff14', '#00ff7f', '#008080', '#36454f', '#F88379', '#Ff4500',
3             '#Faf0e6', '#8c92ac', '#Dbd7d2', '#A7a6ba', '#B38b6d']
```

In [41]:

```
1 import random
```



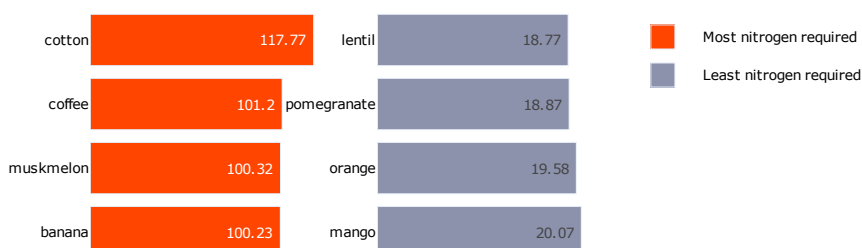
In [42]:

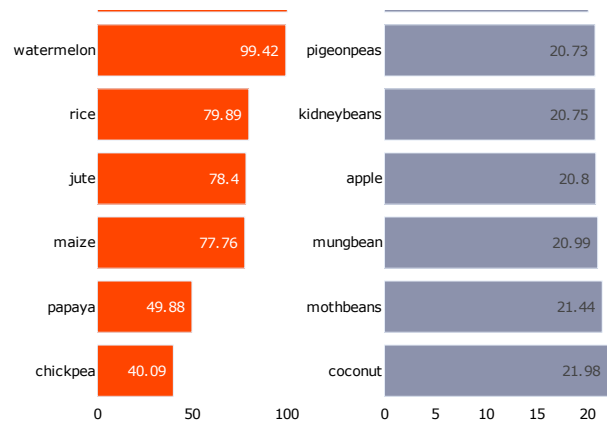
```

1 crop_summary_N = crop_summary.sort_values(by='N',
2                                             ascending=False)
3
4 fig = make_subplots(rows=1, cols=2)
5
6 top = {
7     'y' : crop_summary_N['N'][0:10].sort_values().index,
8     'x' : crop_summary_N['N'][0:10].sort_values()
9 }
10
11 last = {
12     'y' : crop_summary_N['N'][-10:].index,
13     'x' : crop_summary_N['N'][-10:]
14 }
15
16 fig.add_trace(
17     go.Bar(top,
18             name="Most nitrogen required",
19             marker_color=random.choice(colorarr),
20             orientation='h',
21             text=top['x']),
22     row=1, col=1
23 )
24
25 fig.add_trace(
26     go.Bar(last,
27             name="Least nitrogen required",
28             marker_color=random.choice(colorarr),
29             orientation='h',
30             text=last['x']),
31     row=1, col=2
32 )
33
34 fig.update_traces(texttemplate='%{text}', textposition='inside')
35 fig.update_layout(title_text="Nitrogen (N)",
36                   plot_bgcolor='white',
37                   font_size=7,
38                   font_color='black',
39                   height=500)
40
41 fig.update_xaxes(showgrid=False)
42 fig.update_yaxes(showgrid=False)
43 fig.show()

```

Nitrogen (N)





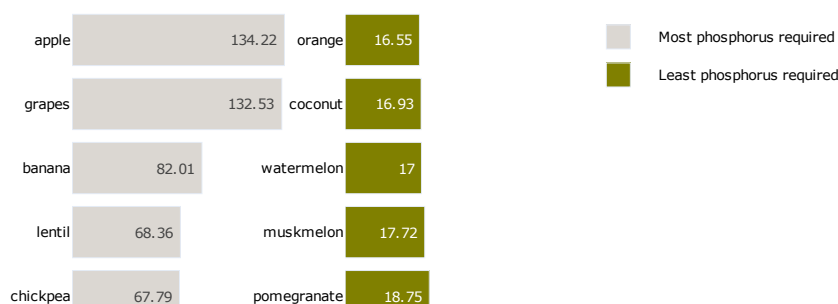
In [43]:

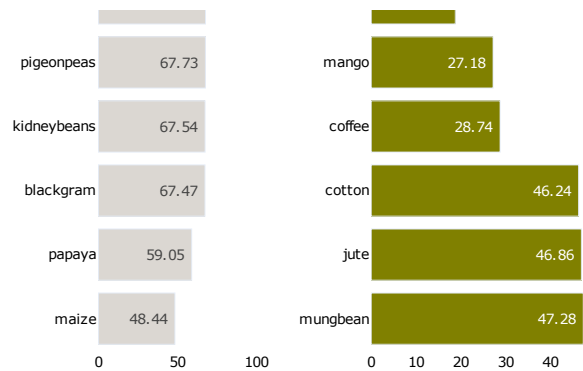
```

1 crop_summary_P = crop_summary.sort_values(by='P', ascending=False)
2
3 fig = make_subplots(rows=1, cols=2)
4
5 top = {
6     'y' : crop_summary_P['P'][0:10].sort_values().index,
7     'x' : crop_summary_P['P'][0:10].sort_values()
8 }
9
10 last = {
11     'y' : crop_summary_P['P'][-10:].index,
12     'x' : crop_summary_P['P'][-10:]
13 }
14
15 fig.add_trace(
16     go.Bar(top,
17             name="Most phosphorus required",
18             marker_color=random.choice(colorarr),
19             orientation='h',
20             text=top['x']),
21     row=1, col=1
22 )
23
24 fig.add_trace(
25     go.Bar(last,
26             name="Least phosphorus required",
27             marker_color=random.choice(colorarr),
28             orientation='h',
29             text=last['x']),
30     row=1, col=2
31 )
32
33 fig.update_traces(texttemplate='%{text}', textposition='inside')
34 fig.update_layout(title_text="Phosphorus (P)",
35                   plot_bgcolor='white',
36                   font_size=7,
37                   font_color='black',
38                   height=500)
39
40 fig.update_xaxes(showgrid=False)
41 fig.update_yaxes(showgrid=False)
42 fig.show()

```

Phosphorus (P)





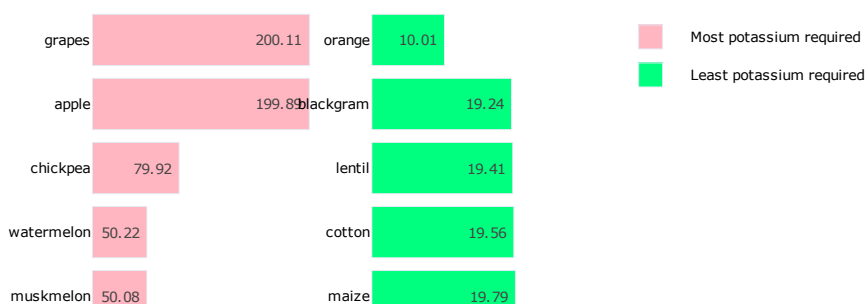
In [44]:

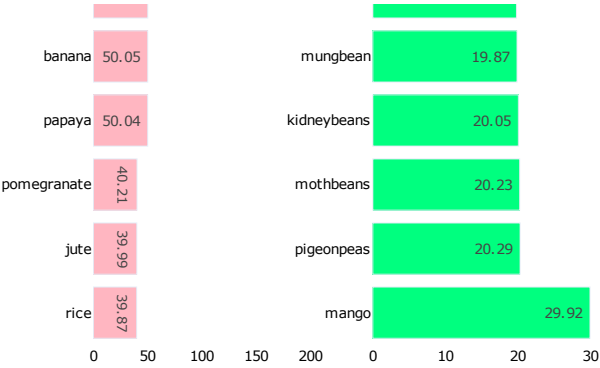
```

1 crop_summary_K = crop_summary.sort_values(by='K', ascending=False)
2
3 fig = make_subplots(rows=1, cols=2)
4
5 top = {
6     'y' : crop_summary_K['K'][0:10].sort_values().index,
7     'x' : crop_summary_K['K'][0:10].sort_values()
8 }
9
10 last = {
11     'y' : crop_summary_K['K'][-10:].index,
12     'x' : crop_summary_K['K'][-10:]
13 }
14
15 fig.add_trace(
16     go.Bar(top,
17             name="Most potassium required",
18             marker_color=random.choice(colorarr),
19             orientation='h',
20             text=top['x']),
21     row=1, col=1
22 )
23
24 fig.add_trace(
25     go.Bar(last,
26             name="Least potassium required",
27             marker_color=random.choice(colorarr),
28             orientation='h',
29             text=last['x']),
30     row=1, col=2
31 )
32
33 fig.update_traces(texttemplate='%{text}', textposition='inside')
34 fig.update_layout(title_text="Potassium (K)",
35                   plot_bgcolor='white',
36                   font_size=7,
37                   font_color='black',
38                   height=500)
39
40 fig.update_xaxes(showgrid=False)
41 fig.update_yaxes(showgrid=False)
42 fig.show()

```

Potassium (K)





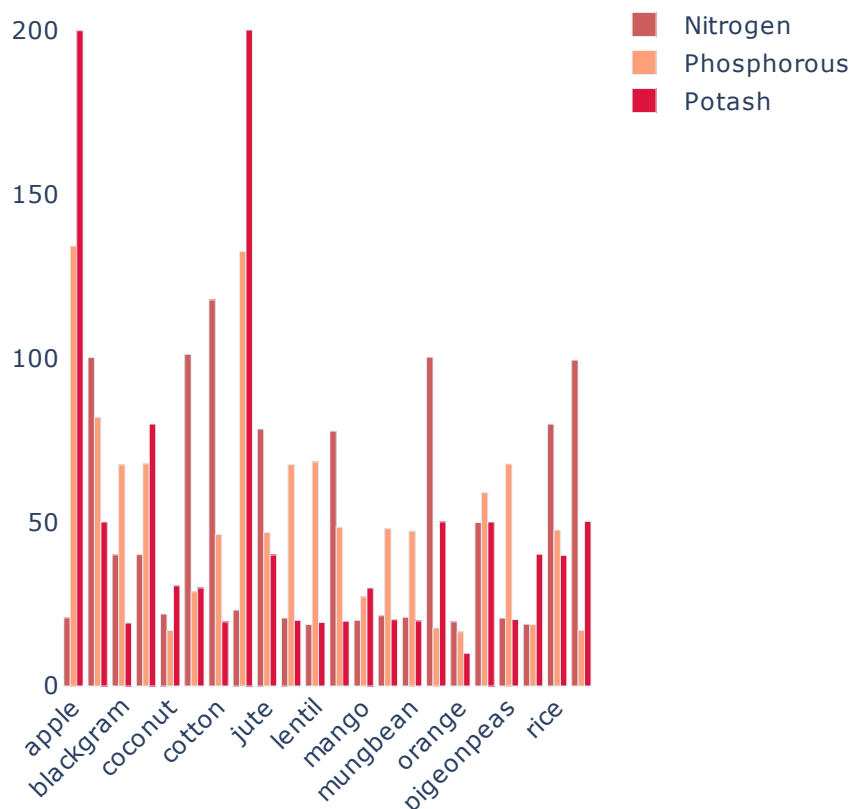
In [45]:

```

1 fig = go.Figure()
2 fig.add_trace(go.Bar(
3     x=crop_summary.index,
4     y=crop_summary['N'],
5     name='Nitrogen',
6     marker_color='indianred'
7 ))
8 fig.add_trace(go.Bar(
9     x=crop_summary.index,
10    y=crop_summary['P'],
11    name='Phosphorous',
12    marker_color='lightsalmon'
13 ))
14 fig.add_trace(go.Bar(
15    x=crop_summary.index,
16    y=crop_summary['K'],
17    name='Potash',
18    marker_color='crimson'
19 ))
20
21 fig.update_layout(title="N, P, K values comparision between crops",
22                   plot_bgcolor='white',
23                   barmode='group',
24                   axis_tickangle=-45)
25
26 fig.show()

```

## N, P, K values comparision between crops







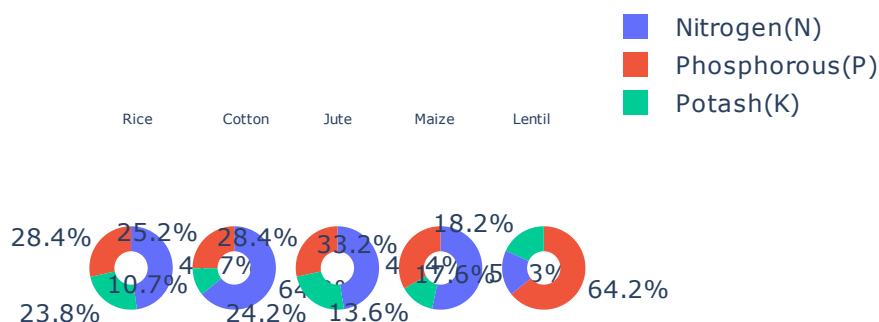
In [46]:

```

1 labels = ['Nitrogen(N)', 'Phosphorous(P)', 'Potash(K)']
2 fig = make_subplots(rows=1, cols=5, specs=[[{'type':'domain'}, {'type':'domain'},
3                                             {'type':'domain'}, {'type':'domain'},
4                                             {'type':'domain'}]])
5
6 rice_npk = crop_summary[crop_summary.index=='rice']
7 values = [rice_npk['N'][0], rice_npk['P'][0], rice_npk['K'][0]]
8 fig.add_trace(go.Pie(labels=labels, values=values,name="Rice"),1, 1)
9
10 cotton_npk = crop_summary[crop_summary.index=='cotton']
11 values = [cotton_npk['N'][0], cotton_npk['P'][0], cotton_npk['K'][0]]
12 fig.add_trace(go.Pie(labels=labels, values=values,name="Cotton"),1, 2)
13
14 jute_npk = crop_summary[crop_summary.index=='jute']
15 values = [jute_npk['N'][0], jute_npk['P'][0], jute_npk['K'][0]]
16 fig.add_trace(go.Pie(labels=labels, values=values,name="Jute"),1, 3)
17
18 maize_npk = crop_summary[crop_summary.index=='maize']
19 values = [maize_npk['N'][0], maize_npk['P'][0], maize_npk['K'][0]]
20 fig.add_trace(go.Pie(labels=labels, values=values,name="Maize"),1, 4)
21
22 lentil_npk = crop_summary[crop_summary.index=='lentil']
23 values = [lentil_npk['N'][0], lentil_npk['P'][0], lentil_npk['K'][0]]
24 fig.add_trace(go.Pie(labels=labels, values=values,name="Lentil"),1, 5)
25
26 fig.update_traces(hole=.4, hoverinfo="label+percent+name")
27 fig.update_layout(
28     title_text="NPK ratio for rice, cotton, jute, maize, lentil",
29     annotations=[dict(text='Rice',x=0.06,y=0.8, font_size=7, showarrow=False),
30                  dict(text='Cotton',x=0.26,y=0.8, font_size=7, showarrow=False),
31                  dict(text='Jute',x=0.50,y=0.8, font_size=7, showarrow=False),
32                  dict(text='Maize',x=0.74,y=0.8, font_size=7, showarrow=False),
33                  dict(text='Lentil',x=0.94,y=0.8, font_size=7, showarrow=False)])
34 fig.show()

```

## NPK ratio for rice, cotton, jute, maize, lentil





In [48]:

```

Nitrogen(N)', 'Phosphorous(P)', 'Potash(K)']
{'type': 'domain'}, {'type': 'domain'}, {'type': 'domain'}, {'type': 'domain'}, {'type': 'domain'}, {'type': 'domain'}, {'type': 'domain'}, {'type': 'domain'}, {'type': 'domain'}
subplots(rows=2, cols=5, specs=specs)
= ['rgb(255, 128, 0)', 'rgb(0, 153, 204)', 'rgb(173, 173, 133)']

= crop_summary[crop_summary.index=='apple']
apple_npk['N'][0], apple_npk['P'][0], apple_npk['K'][0]]
ace(go.Pie(labels=labels, values=values, name="Apple", marker_colors=cafe_colors), 1, 1)

= crop_summary[crop_summary.index=='banana']
banana_npk['N'][0], banana_npk['P'][0], banana_npk['K'][0]]
ace(go.Pie(labels=labels, values=values, name="Banana", marker_colors=cafe_colors), 1, 2)

= crop_summary[crop_summary.index=='grapes']
grapes_npk['N'][0], grapes_npk['P'][0], grapes_npk['K'][0]]
ace(go.Pie(labels=labels, values=values, name="Grapes", marker_colors=cafe_colors), 1, 3)

= crop_summary[crop_summary.index=='orange']
orange_npk['N'][0], orange_npk['P'][0], orange_npk['K'][0]]
ace(go.Pie(labels=labels, values=values, name="Orange", marker_colors=cafe_colors), 1, 4)

= crop_summary[crop_summary.index=='mango']
mango_npk['N'][0], mango_npk['P'][0], mango_npk['K'][0]]
ace(go.Pie(labels=labels, values=values, name="Mango", marker_colors=cafe_colors), 1, 5)

= crop_summary[crop_summary.index=='coconut']
coconut_npk['N'][0], coconut_npk['P'][0], coconut_npk['K'][0]]
ace(go.Pie(labels=labels, values=values, name="Coconut", marker_colors=cafe_colors), 2, 1)

= crop_summary[crop_summary.index=='papaya']
papaya_npk['N'][0], papaya_npk['P'][0], papaya_npk['K'][0]]
ace(go.Pie(labels=labels, values=values, name="Papaya", marker_colors=cafe_colors), 2, 2)

= crop_summary[crop_summary.index=='pomegranate']
pomegranate_npk['N'][0], pomegranate_npk['P'][0], pomegranate_npk['K'][0]]
ace(go.Pie(labels=labels, values=values, name="Pomegranate", marker_colors=cafe_colors), 2, 3)

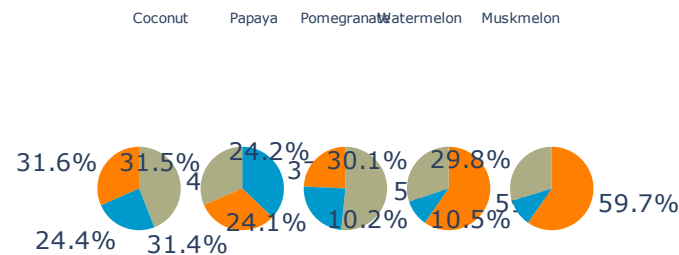
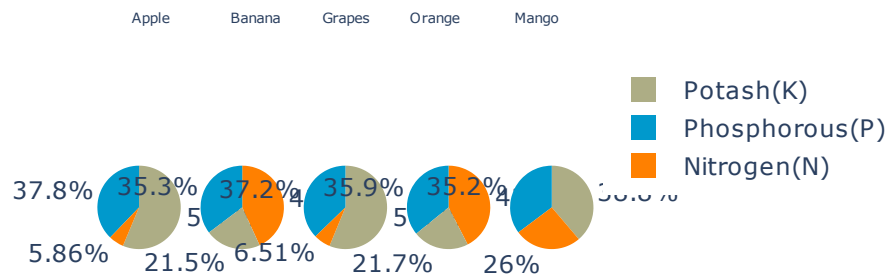
= crop_summary[crop_summary.index=='watermelon']
watermelon_npk['N'][0], watermelon_npk['P'][0], watermelon_npk['K'][0]]
ace(go.Pie(labels=labels, values=values, name="Watermelon", marker_colors=cafe_colors), 2, 4)

= crop_summary[crop_summary.index=='muskmelon']
muskmelon_npk['N'][0], muskmelon_npk['P'][0], muskmelon_npk['K'][0]]
ace(go.Pie(labels=labels, values=values, name="Muskmelon", marker_colors=cafe_colors), 2, 5)

layout(
text="NPK ratio for fruits",
figspecs=[dict(text='Apple', x=0.06, y=1.08, font_size=7, showarrow=False),
dict(text='Banana', x=0.26, y=1.08, font_size=7, showarrow=False),
dict(text='Grapes', x=0.50, y=1.08, font_size=7, showarrow=False),
dict(text='Orange', x=0.74, y=1.08, font_size=7, showarrow=False),
dict(text='Mango', x=0.94, y=1.08, font_size=7, showarrow=False),
dict(text='Coconut', x=0.06, y=0.46, font_size=7, showarrow=False),
dict(text='Papaya', x=0.26, y=0.46, font_size=7, showarrow=False),
dict(text='Pomegranate', x=0.50, y=0.46, font_size=7, showarrow=False),
dict(text='Watermelon', x=0.74, y=0.46, font_size=7, showarrow=False),
dict(text='Muskmelon', x=0.94, y=0.46, font_size=7, showarrow=False)])

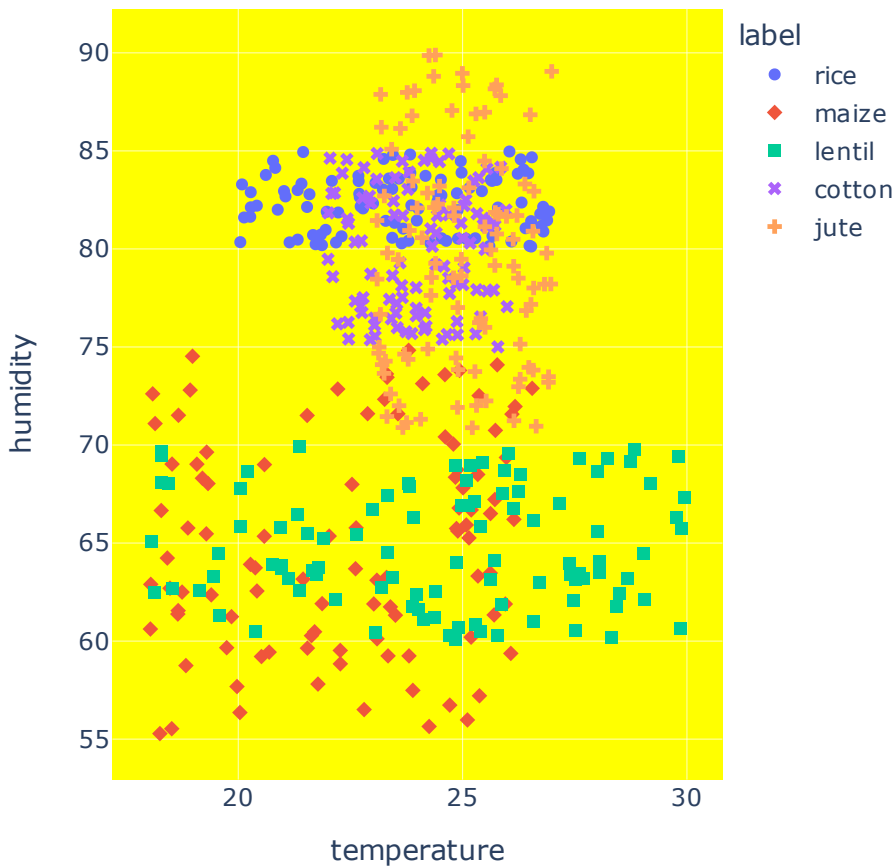
```

# NPK ratio for fruits



In [51]:

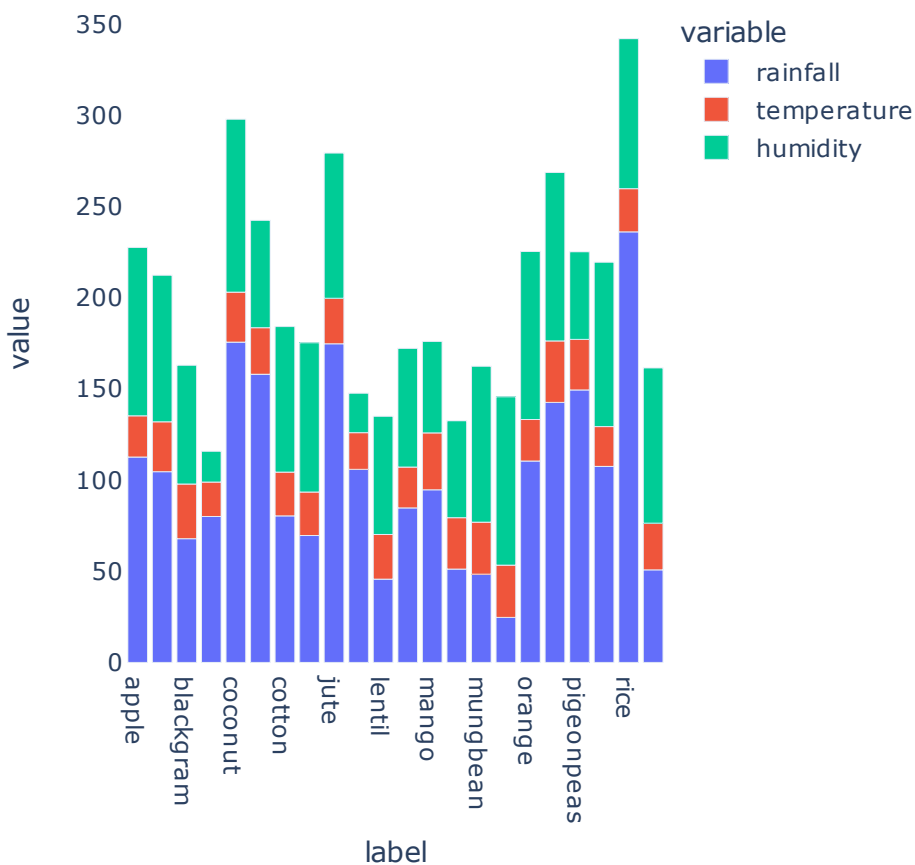
```
1 crop_scatter = data[(data['label']=='rice') |  
2                       (data['label']=='jute') |  
3                       (data['label']=='cotton') |  
4                       (data['label']=='maize') |  
5                       (data['label']=='lentil')]  
6  
7 fig = px.scatter(crop_scatter, x="temperature", y="humidity", color="label", symbol=  
8 fig.update_layout(plot_bgcolor='yellow')  
9 fig.update_xaxes(showgrid=True)  
10 fig.update_yaxes(showgrid=True)  
11  
12 fig.show()
```



In [52]:

```
1 fig = px.bar(crop_summary, x=crop_summary.index, y=["rainfall", "temperature", "humidit  
2 fig.update_layout(title_text="Comparision between rainfall, temerature and humidity  
3                     plot_bgcolor='white',  
4                     height=500)  
5  
6 fig.update_xaxes(showgrid=False)  
7 fig.update_yaxes(showgrid=False)  
8 fig.show()
```

## Comparision between rainfall, temerature and humidity



In [53]:

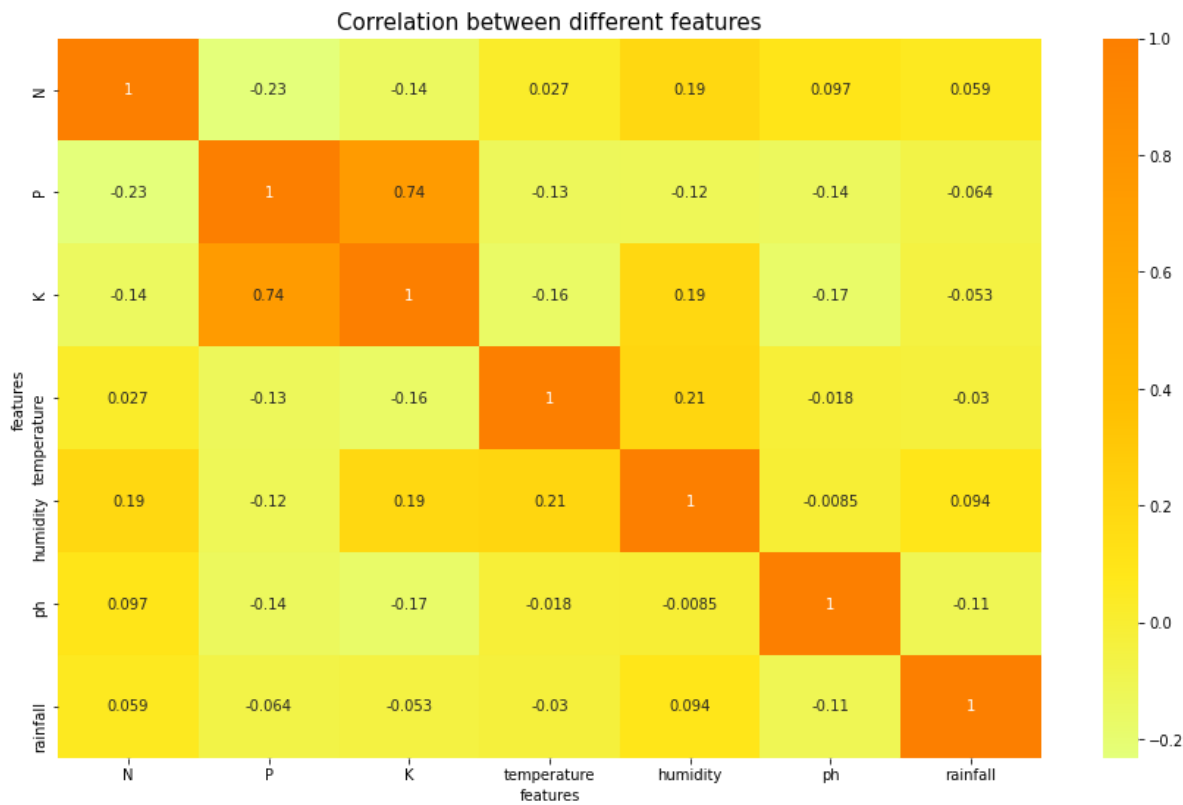
```
1 data.corr()
```

Out[53]:

	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 [54]:

```
1 fig, ax = plt.subplots(1, 1, figsize=(15, 9))
2 sns.heatmap(data.corr(), annot=True,cmap='Wistia')
3 ax.set(xlabel='features')
4 ax.set(ylabel='features')
5
6 plt.title('Correlation between different features', fontsize = 15, c='black')
7 plt.show()
```



In [55]:

```
1 X = data.drop('label', axis=1)
2 y = data['label']
```

In [56]:

```
1 from sklearn.model_selection import train_test_split
2 X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.33,
3                                                    shuffle = True, random_state = 0)
```

In [57]:

```
1 import lightgbm as lgb
2 model = lgb.LGBMClassifier()
3 model.fit(X_train, y_train)
```

Out[57]:

LGBMClassifier()

In [58]:

```
1 y_pred=model.predict(X_test)
```

In [59]:

```
1 from sklearn.metrics import accuracy_score
2 accuracy=accuracy_score(y_pred, y_test)
3 print('LightGBM Model accuracy score: {0:0.4f}'.format(accuracy_score(y_test, y_pred)))
```

LightGBM Model accuracy score: 0.9890

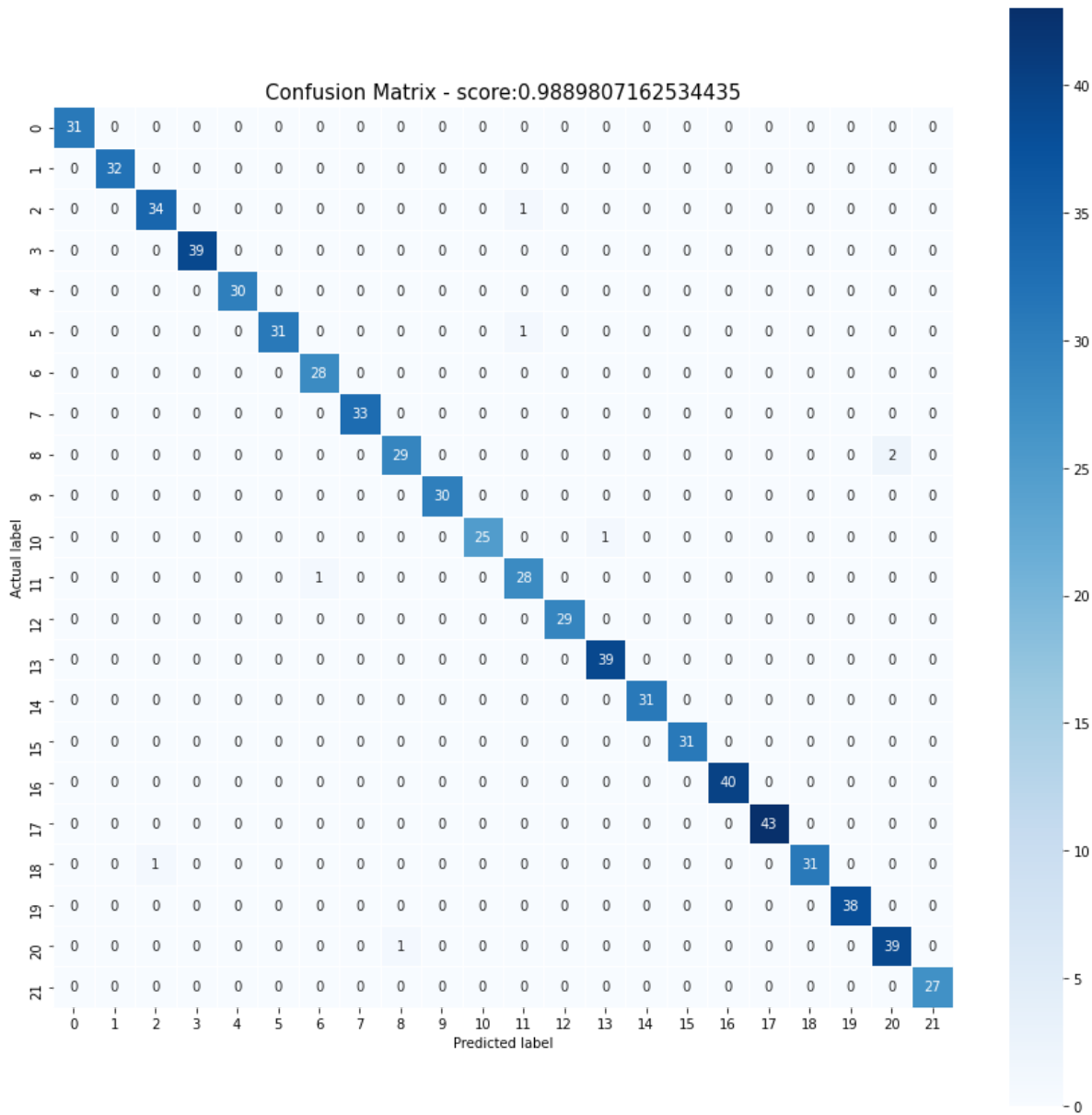


In [60]:

```

1 from sklearn.metrics import confusion_matrix
2 cm = confusion_matrix(y_test, y_pred)
3 plt.figure(figsize=(15,15))
4 sns.heatmap(cm, annot=True, fmt=".0f", linewidths=.5, square = True, cmap = 'Blues')
5 plt.ylabel('Actual label');
6 plt.xlabel('Predicted label');
7 all_sample_title = 'Confusion Matrix - score:'+str(accuracy_score(y_test,y_pred))
8 plt.title(all_sample_title, size = 15);
9 plt.show()

```



In [61]:



```
1 from sklearn.metrics import classification_report
2 print(classification_report(y_test, y_pred))
```

	precision	recall	f1-score	support
apple	1.00	1.00	1.00	31
banana	1.00	1.00	1.00	32
blackgram	0.97	0.97	0.97	35
chickpea	1.00	1.00	1.00	39
coconut	1.00	1.00	1.00	30
coffee	1.00	0.97	0.98	32
cotton	0.97	1.00	0.98	28
grapes	1.00	1.00	1.00	33
jute	0.97	0.94	0.95	31
kidneybeans	1.00	1.00	1.00	30
lentil	1.00	0.96	0.98	26
maize	0.93	0.97	0.95	29
mango	1.00	1.00	1.00	29
mothbeans	0.97	1.00	0.99	39
mungbean	1.00	1.00	1.00	31
muskmelon	1.00	1.00	1.00	31
orange	1.00	1.00	1.00	40
papaya	1.00	1.00	1.00	43
pigeonpeas	1.00	0.97	0.98	32
pomegranate	1.00	1.00	1.00	38
rice	0.95	0.97	0.96	40
watermelon	1.00	1.00	1.00	27
accuracy			0.99	726
macro avg	0.99	0.99	0.99	726
weighted avg	0.99	0.99	0.99	726

In [80]:



```
1 from sklearn.tree import DecisionTreeClassifier
2 classifier= DecisionTreeClassifier(criterion='entropy', random_state=0)
3 classifier.fit(X_train, y_train)
```

Out[80]:

DecisionTreeClassifier(criterion='entropy', random\_state=0)

In [81]:



```
1 y_pred=classifier.predict(X_test)
```

In [82]:



```
1 from sklearn.metrics import accuracy_score
2 accuracy=accuracy_score(y_pred, y_test)
3 print('Decision Tree Model accuracy score: {0:0.4f}'.format(accuracy_score(y_test, y_test)))
```

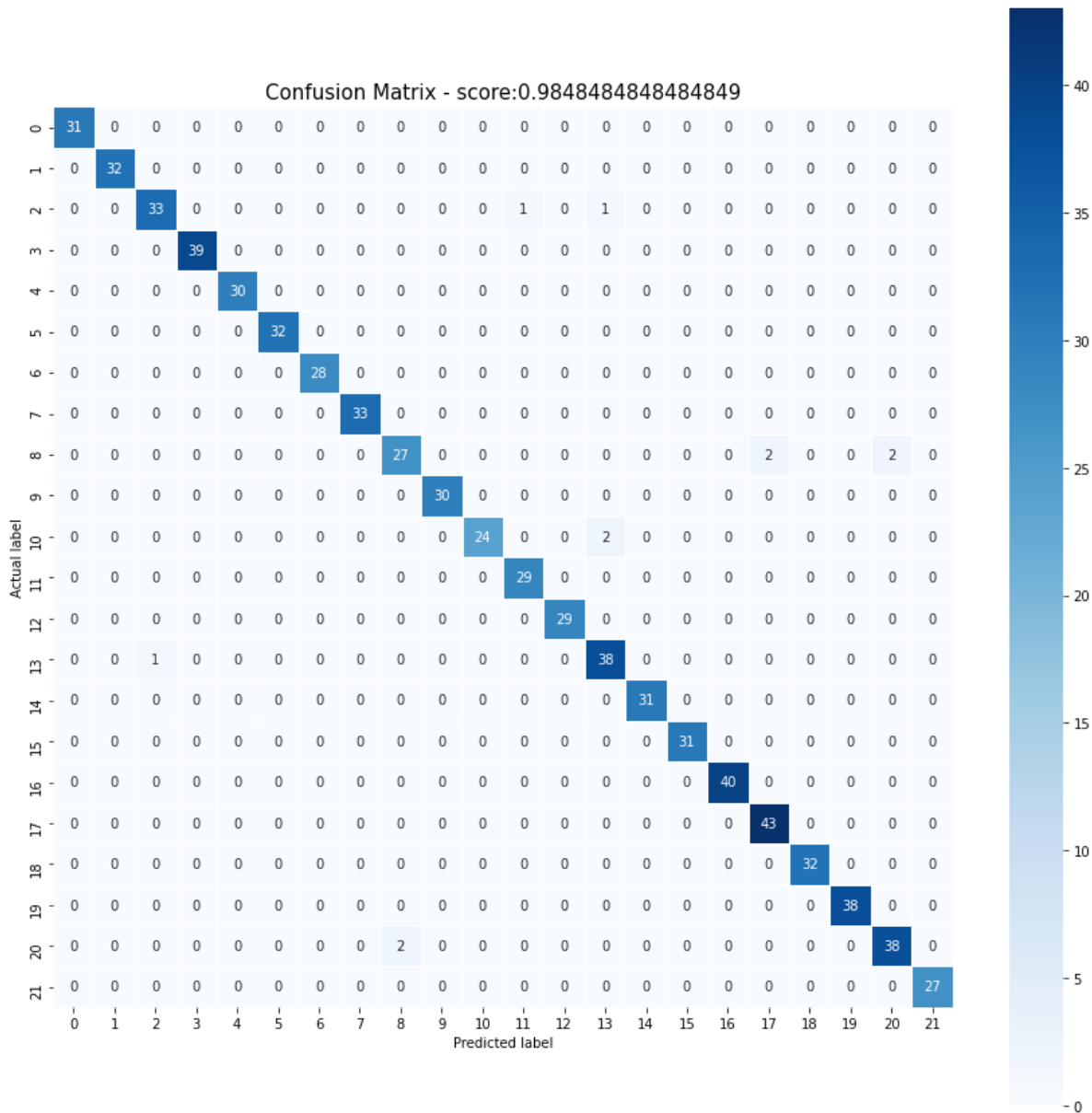
Decision Tree Model accuracy score: 0.9848

In [83]:

```

1 from sklearn.metrics import confusion_matrix
2 cm = confusion_matrix(y_test, y_pred)
3 plt.figure(figsize=(15,15))
4 sns.heatmap(cm, annot=True, fmt=".0f", linewidths=.5, square = True, cmap = 'Blues')
5 plt.ylabel('Actual label');
6 plt.xlabel('Predicted label');
7 all_sample_title = 'Confusion Matrix - score:' + str(accuracy_score(y_test,y_pred))
8 plt.title(all_sample_title, size = 15);
9 plt.show()

```



In [84]:



```
1 from sklearn.metrics import classification_report
2 print(classification_report(y_test, y_pred))
```

	precision	recall	f1-score	support
apple	1.00	1.00	1.00	31
banana	1.00	1.00	1.00	32
blackgram	0.97	0.94	0.96	35
chickpea	1.00	1.00	1.00	39
coconut	1.00	1.00	1.00	30
coffee	1.00	1.00	1.00	32
cotton	1.00	1.00	1.00	28
grapes	1.00	1.00	1.00	33
jute	0.93	0.87	0.90	31
kidneybeans	1.00	1.00	1.00	30
lentil	1.00	0.92	0.96	26
maize	0.97	1.00	0.98	29
mango	1.00	1.00	1.00	29
mothbeans	0.93	0.97	0.95	39
mungbean	1.00	1.00	1.00	31
muskmelon	1.00	1.00	1.00	31
orange	1.00	1.00	1.00	40
papaya	0.96	1.00	0.98	43
pigeonpeas	1.00	1.00	1.00	32
pomegranate	1.00	1.00	1.00	38
rice	0.95	0.95	0.95	40
watermelon	1.00	1.00	1.00	27
accuracy			0.98	726
macro avg	0.99	0.98	0.99	726
weighted avg	0.98	0.98	0.98	726

In [85]:



```
1 from sklearn.ensemble import RandomForestClassifier
2 classifier_rf= RandomForestClassifier(n_estimators= 10, criterion="entropy")
3 classifier_rf.fit(X_train, y_train)
```

Out[85]:

RandomForestClassifier(criterion='entropy', n\_estimators=10)

In [86]:



```
1 y_pred= classifier_rf.predict(X_test)
```

In [87]:

```

1 from sklearn.metrics import accuracy_score
2 accuracy=accuracy_score(y_pred, y_test)
3 print('Random Forest Model accuracy score: {0:0.4f}'.format(accuracy_score(y_test,

```

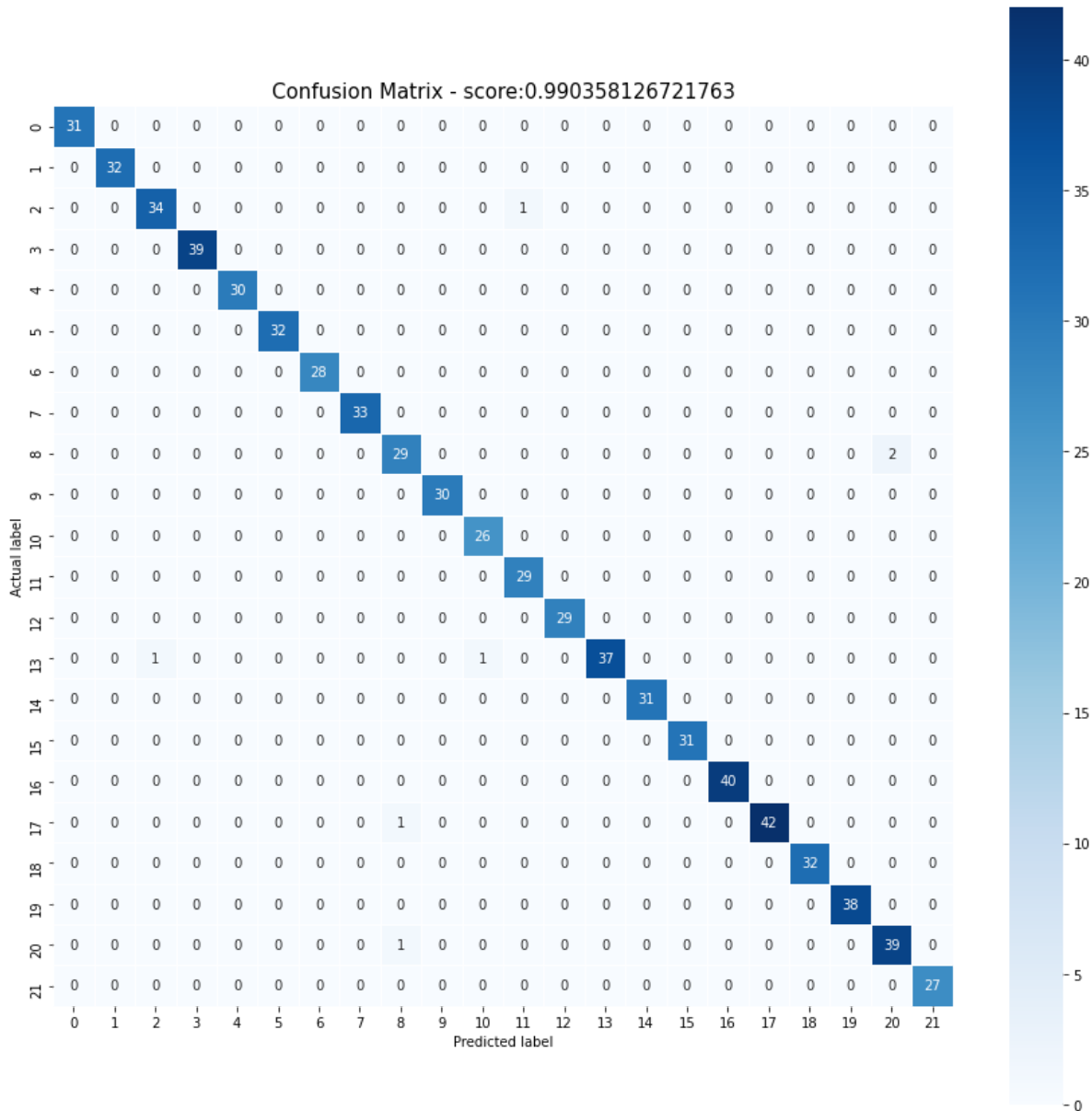
Random Forest Model accuracy score: 0.9904

In [88]:

```

1 from sklearn.metrics import confusion_matrix
2 cm = confusion_matrix(y_test, y_pred)
3 plt.figure(figsize=(15,15))
4 sns.heatmap(cm, annot=True, fmt=".0f", linewidths=.5, square = True, cmap = 'Blues')
5 plt.ylabel('Actual label');
6 plt.xlabel('Predicted label');
7 all_sample_title = 'Confusion Matrix - score:'+str(accuracy_score(y_test,y_pred))
8 plt.title(all_sample_title, size = 15);
9 plt.show()

```



In [89]:

```
1 from sklearn.metrics import classification_report
2 print(classification_report(y_test, y_pred))
```

	precision	recall	f1-score	support
apple	1.00	1.00	1.00	31
banana	1.00	1.00	1.00	32
blackgram	0.97	0.97	0.97	35
chickpea	1.00	1.00	1.00	39
coconut	1.00	1.00	1.00	30
coffee	1.00	1.00	1.00	32
cotton	1.00	1.00	1.00	28
grapes	1.00	1.00	1.00	33
jute	0.94	0.94	0.94	31
kidneybeans	1.00	1.00	1.00	30
lentil	0.96	1.00	0.98	26
maize	0.97	1.00	0.98	29
mango	1.00	1.00	1.00	29
mothbeans	1.00	0.95	0.97	39
mungbean	1.00	1.00	1.00	31
muskmelon	1.00	1.00	1.00	31
orange	1.00	1.00	1.00	40
papaya	1.00	0.98	0.99	43
pigeonpeas	1.00	1.00	1.00	32
pomegranate	1.00	1.00	1.00	38
rice	0.95	0.97	0.96	40
watermelon	1.00	1.00	1.00	27
accuracy			0.99	726
macro avg	0.99	0.99	0.99	726
weighted avg	0.99	0.99	0.99	726

In [79]:

```
1 from sklearn.linear_model import LogisticRegression
2 classifier_lr = LogisticRegression(random_state = 0)
3 classifier_lr.fit(X_train, y_train)
```

Out[79]:

LogisticRegression(random\_state=0)

In [75]:

```
1 y_pred = classifier_lr.predict(X_test)
```

In [76]:

```
1 from sklearn.metrics import accuracy_score
2 accuracy=accuracy_score(y_pred, y_test)
3 print('Logistic Regression Model accuracy score: {0:0.4f}'.format(accuracy_score(y_
```

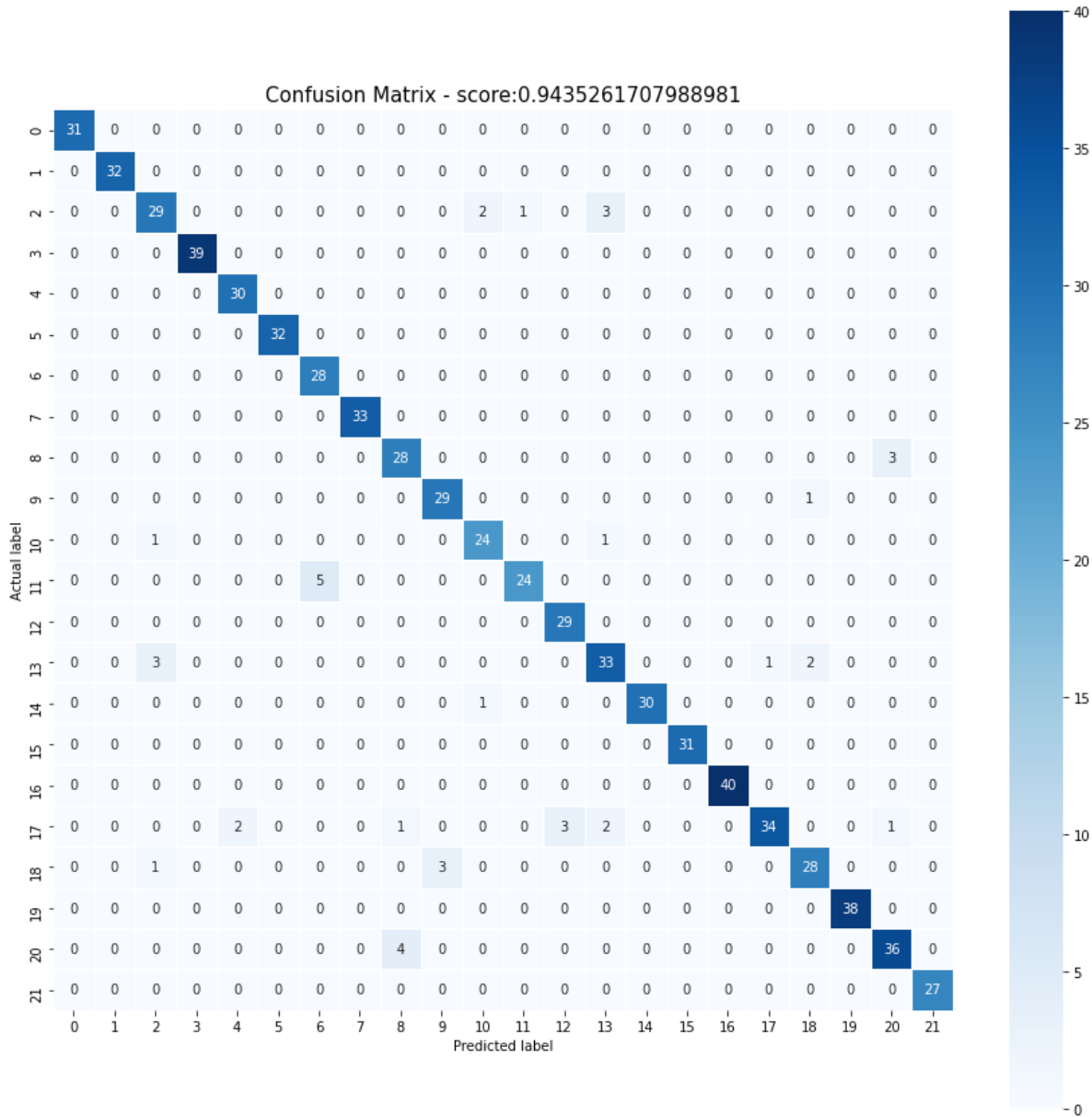
Logistic Regression Model accuracy score: 0.9435

In [78]:

```

1 from sklearn.metrics import confusion_matrix
2 cm = confusion_matrix(y_test, y_pred)
3 plt.figure(figsize=(15,15))
4 sns.heatmap(cm, annot=True, fmt=".0f", linewidths=.5, square = True, cmap = 'Blues')
5 plt.ylabel('Actual label');
6 plt.xlabel('Predicted label');
7 all_sample_title = 'Confusion Matrix - score:'+str(accuracy_score(y_test,y_pred))
8 plt.title(all_sample_title, size = 15);
9 plt.show()

```





In [77]:



```
1 from sklearn.metrics import classification_report
2 print(classification_report(y_test, y_pred))
```

	precision	recall	f1-score	support
apple	1.00	1.00	1.00	31
banana	1.00	1.00	1.00	32
blackgram	0.85	0.83	0.84	35
chickpea	1.00	1.00	1.00	39
coconut	0.94	1.00	0.97	30
coffee	1.00	1.00	1.00	32
cotton	0.85	1.00	0.92	28
grapes	1.00	1.00	1.00	33
jute	0.85	0.90	0.88	31
kidneybeans	0.91	0.97	0.94	30
lentil	0.89	0.92	0.91	26
maize	0.96	0.83	0.89	29
mango	0.91	1.00	0.95	29
mothbeans	0.85	0.85	0.85	39
mungbean	1.00	0.97	0.98	31
muskmelon	1.00	1.00	1.00	31
orange	1.00	1.00	1.00	40
papaya	0.97	0.79	0.87	43
pigeonpeas	0.90	0.88	0.89	32
pomegranate	1.00	1.00	1.00	38
rice	0.90	0.90	0.90	40
watermelon	1.00	1.00	1.00	27
accuracy			0.94	726
macro avg	0.94	0.95	0.94	726
weighted avg	0.95	0.94	0.94	726