In [6]:

```
import pandas as pd
import numpy as np
import random
from IPython.core.display import update_display
import matplotlib.pyplot as plt
import plotly.express as px
import plotly.graph_objects as go
import plotly.express as px
from plotly.subplots import make_subplots
import seaborn as sns
import warnings
from sklearn.metrics import accuracy_score
from sklearn.metrics import confusion_matrix
from sklearn.metrics import classification_report
from sklearn.tree import DecisionTreeClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from sklearn.ensemble import VotingClassifier
from sklearn.svm import SVC
from tkinter import *
from tkinter import ttk
from tkinter import messagebox
from PIL import ImageTk, Image
warnings.filterwarnings('ignore')
```

In [7]:

```
data=pd.read_csv('crop_recommendation.csv')
```

In [8]:

```
data.head(5)
```

Out[8]:

	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 [9]:

```
data.tail(5)
```

Out[9]:

	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 [10]:

```
data.shape
```

Out[10]:

```
(2200, 8)
```

In [11]:

```
data.columns
```

Out[11]:

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

In [12]:

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

Out[12]: 0

In [13]:
```
data.isnull().sum()
```

Out[13]:
```
N              0
P              0
K              0
temperature    0
humidity       0
ph             0
rainfall       0
label          0
dtype: int64
```

In [14]:
```
data.info
```

Out[14]:
```
<bound method DataFrame.info of         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 x 8 columns]>
```

In [15]:
```
data.describe()
```

Out[15]:

	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 [16]:
```
data.nunique()
```

Out[16]:
```
N               137
P               117
K                73
temperature    2200
humidity       2200
ph             2200
rainfall       2200
label            22
dtype: int64
```

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

Out[17]:
```
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 [18]:
```
data['label'].value_counts()
```

Out[18]:
```
label
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: count, dtype: int64
```

In [19]:
```
crop_summary=pd.pivot_table(data,index=['label'],aggfunc='mean')
```

In [20]:
```
crop_summary
```

Out[20]:

label	K	N	P	humidity	ph	rainfall	temperature
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 [21]:

```
data.columns
```

Out[21]:

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

BOXPLOT

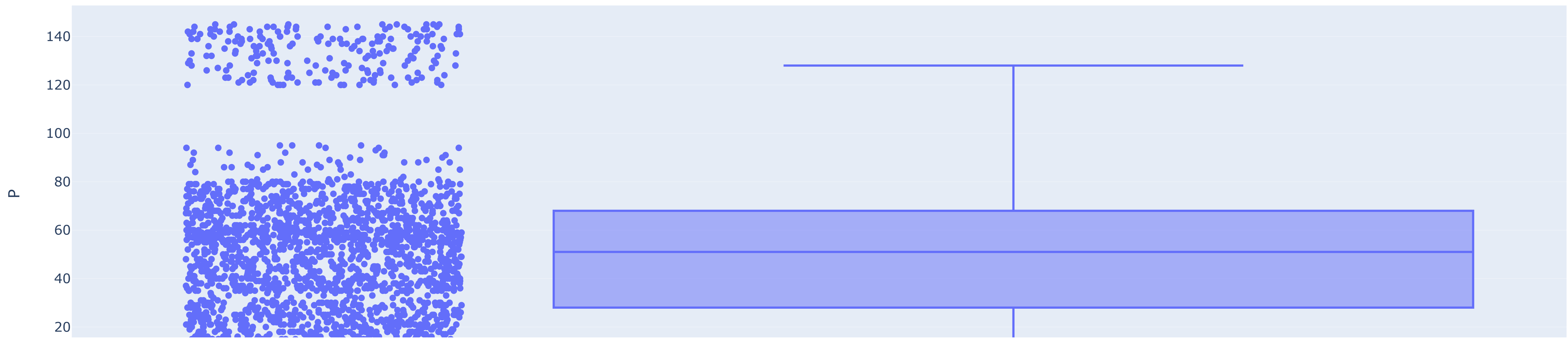
In [18]:

```
#checking and treating outliers in each column

fig =px.box(data,y='N',points='all',title="Boxplot of N")
fig.show()
```

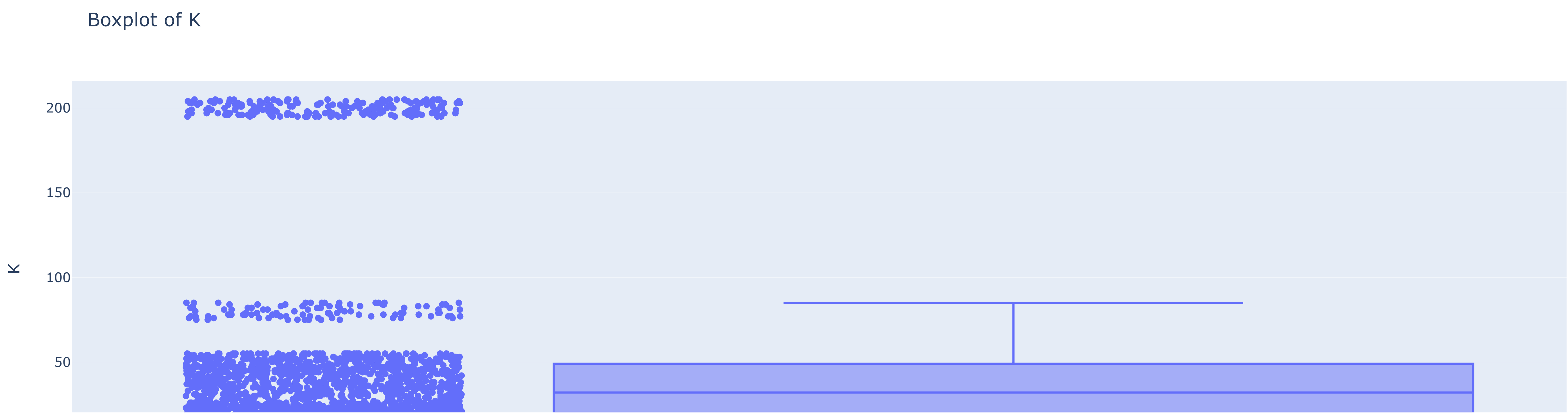
Boxplot of N


```
In [19]: fig= px.box(data, y="P",points="all",title="Boxplot of P")
         # sns.boxplot(data["P"])
         # plt.xticks(rotation=90)
         fig.show()
```

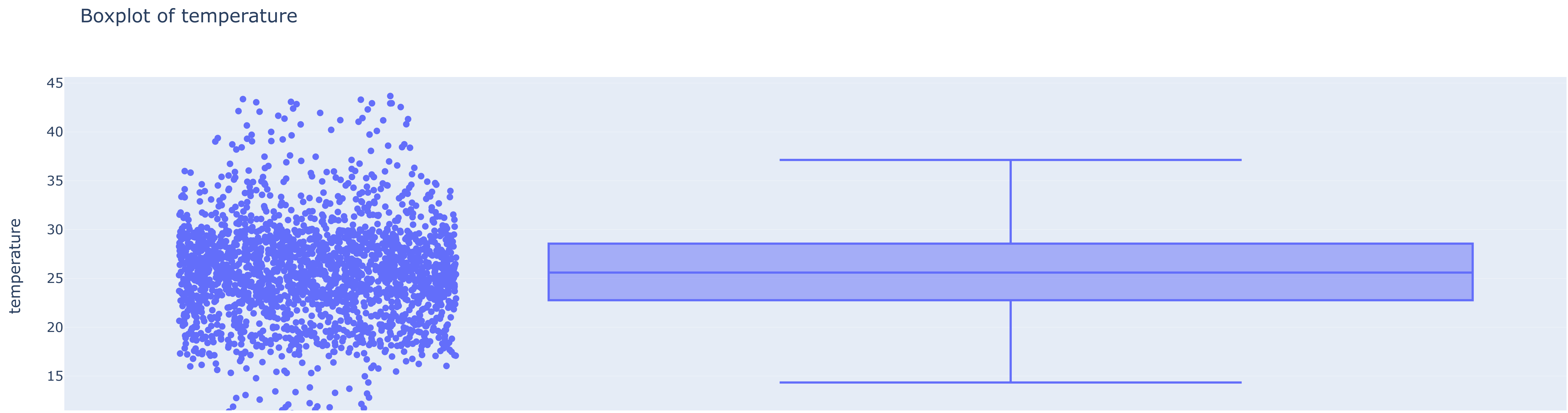
Boxplot of P



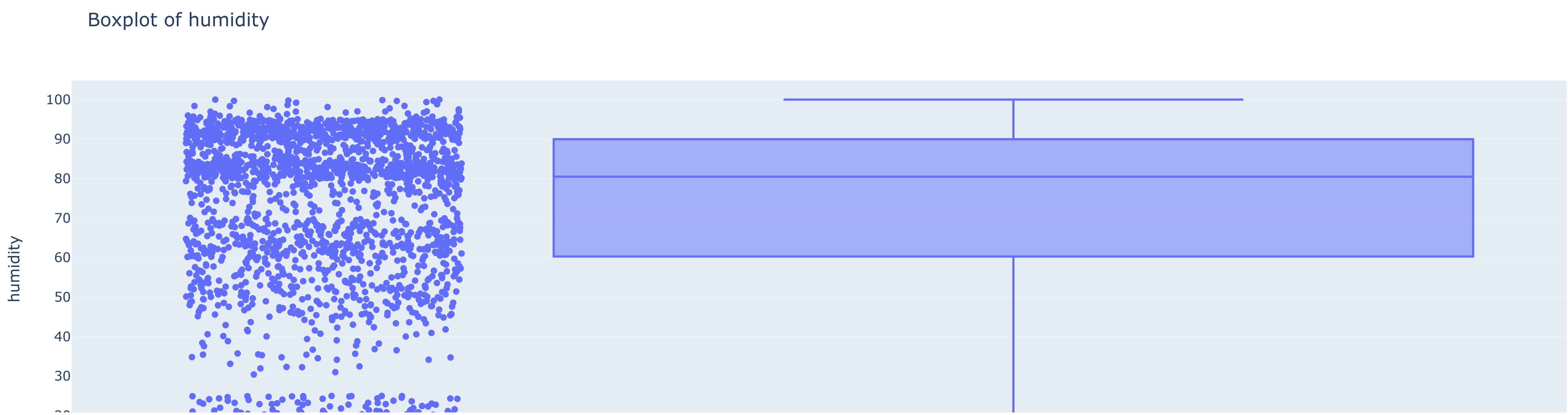
In [20]:
```
fig= px.box(data, y="K",points="all",title="Boxplot of K")
fig.show()
```



In [21]:
```
fig= px.box(data, y="temperature",points="all",title="Boxplot of temperature")
fig.show()
```



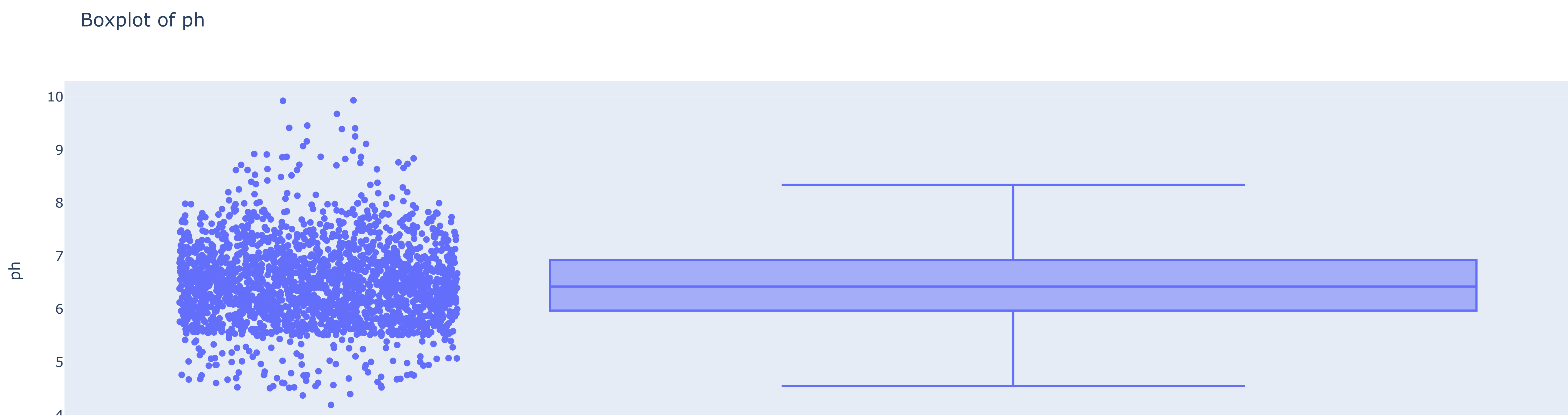
In [22]:
```
fig= px.box(data, y="humidity",points="all",title="Boxplot of humidity")
fig.show()

#boxplot of humidity means that the humidity is between 0.5 and 0.7 for most of the time
#and there are some outliers which are above 0.7 and below 0.5 which are very few in number
```



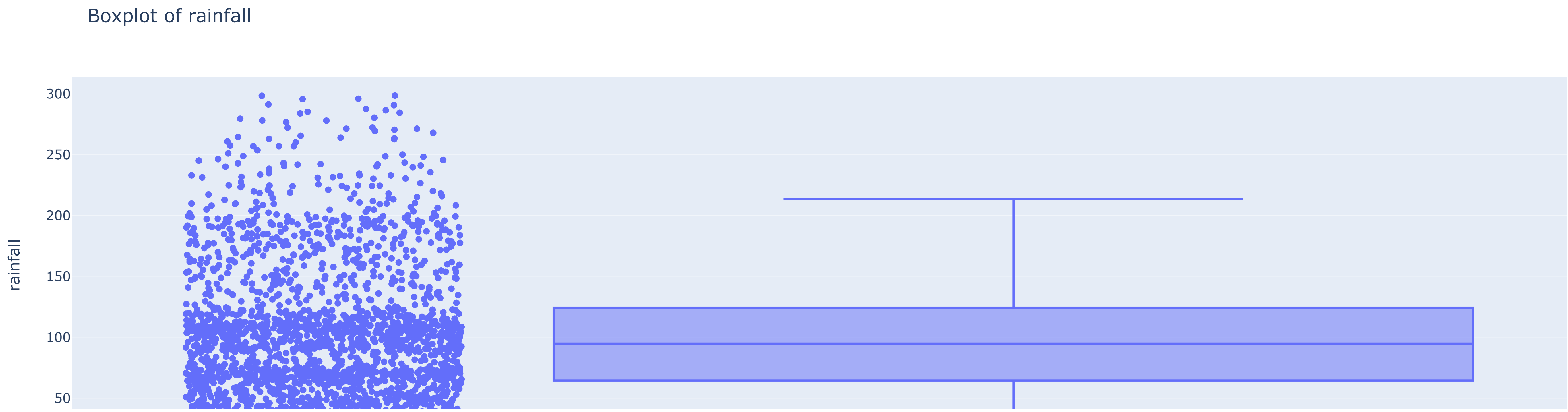
In [23]:
```
data.columns
```

Out[23]:
```
Index(['N', 'P', 'K', 'temperature', 'humidity', 'ph', 'rainfall', 'label'], dtype='object')
```

In [24]:
```
fig= px.box(data, y="ph",points="all",title="Boxplot of ph")
fig.show()

#boxplot of ph means that the ph of the water is between 6.5 and 8.5 and the median is 7.5 and
# the outliers are 0 and 14 which are not possible values for ph of water
```




```
In [25]: fig= px.box(data, y="rainfall",points="all",title="Boxplot of rainfall")
         fig.show()
```



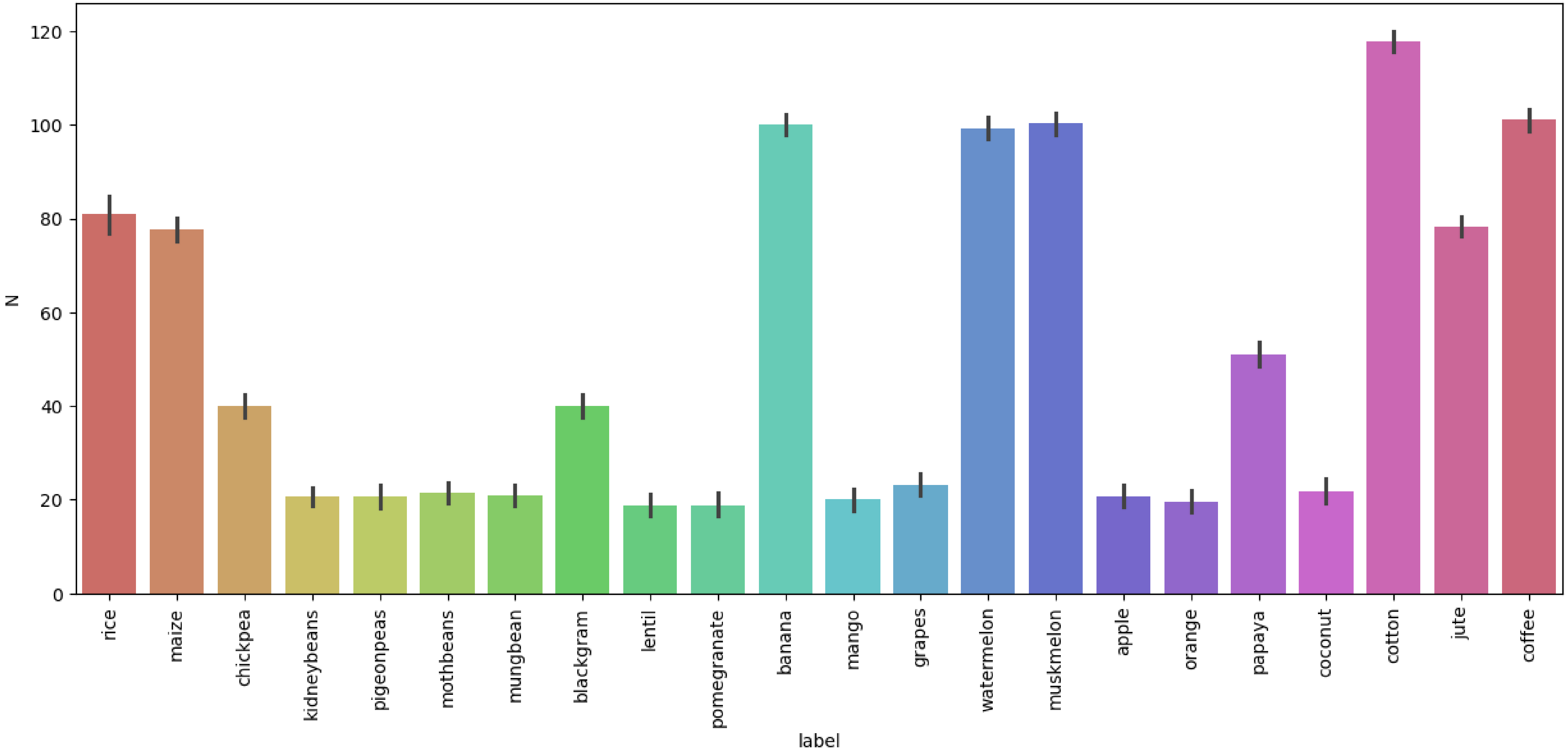
In [26]:
```
#Detection & removal of outliers

df_boston = data
df_boston.columns = df_boston.columns
df_boston.head()

#Detection of Outliers
#IQR = Q3 - Q1
Q1=np.percentile(df_boston['rainfall'],25,interpolation='midpoint') # type: ignore
Q3=np.percentile(df_boston['rainfall'],75,interpolation='midpoint') # type: ignore
IQR=Q3-Q1

print("Old Shape: ", df_boston.shape)

# Upper bound
upper = np.where(df_boston['rainfall'] >= (Q3+1.5*IQR))

# Lower bound
lower = np.where(df_boston['rainfall'] <= (Q1-1.5*IQR))

#Removing the Outlier
df_boston.drop(upper[0], inplace=True)
df_boston.drop(lower[0], inplace=True)


print("New Shape: ", df_boston.shape)
```

```
Old Shape:  (2200, 8)
New Shape:  (2101, 8)
```

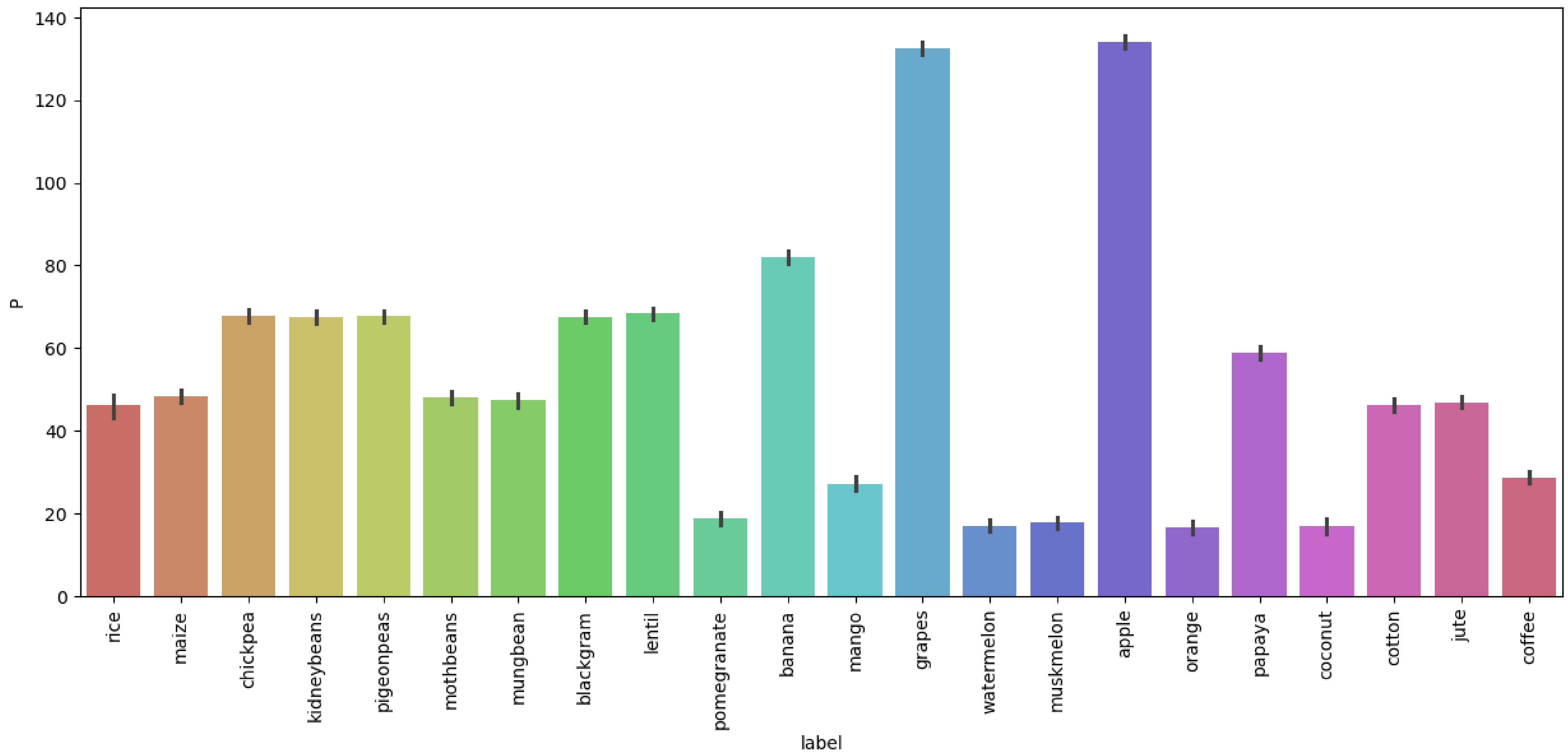
In [27]:
```
data=df_boston
```

In [28]:
```
plt.figure(figsize=(15,6))
sns.barplot(y='N',x='label',data=data,palette='hls')
```

```
plt.xticks(rotation=90)
plt.show()

#This bar plot shows that the nitrogen content is highest in cotton and lowest in lentil
```

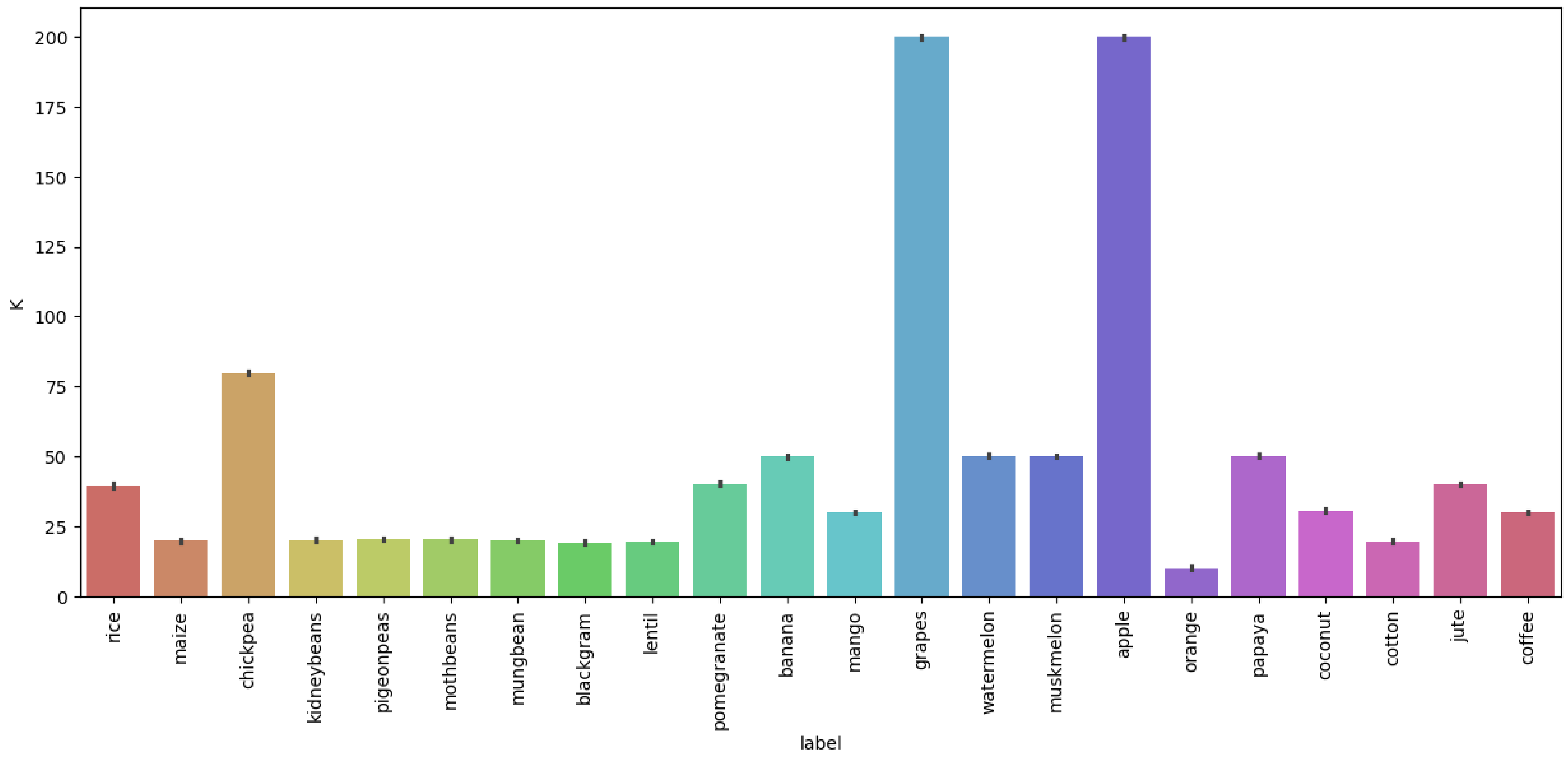


In [29]:
```
plt.figure(figsize=(15,6))
sns.barplot(y='P',x='label',data=data,palette='hls')
plt.xticks(rotation=90)
plt.show()

#This bar plot shows that the phosphorous content is highest in apple and lowest in watermelon.
```



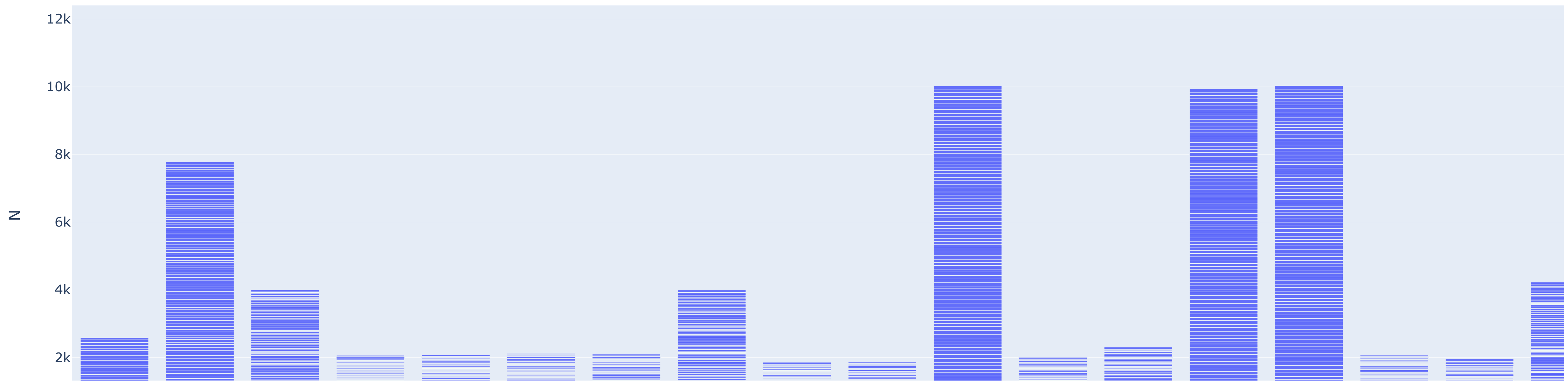
In [30]:

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

#This bar plot shows that the potassium content is highest in grapes and lowest in orange.
```



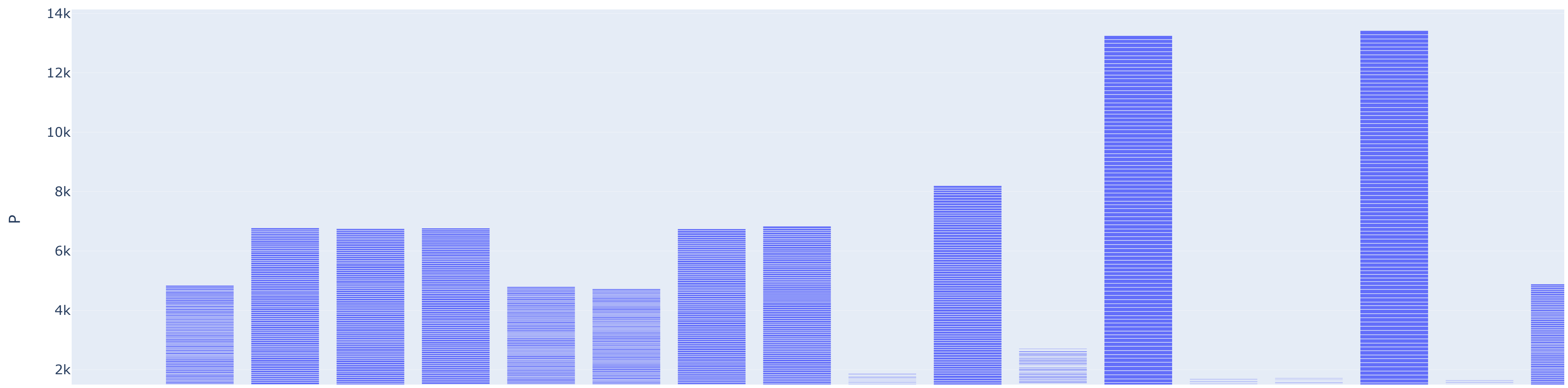
In [31]:
```
crop_summary_new=data.copy()

#we used a variable crop_summary_new to store the data of crop_summary and then we used the variable crop_summary_new to plot the graph
#because if we use crop_summary to plot the graph then the graph will be plotted in the order of the index of crop_summary which is label
#and the order of the index of crop_summary is alphabetical order and we want the graph to be plotted in the order of the yield of the crops
#so we used crop_summary_new to plot the graph
```

In [33]:
```
fig1=px.bar(crop_summary_new,x='label',y='N')
fig1.show()

#this shows that the nitrogen content is highest in cotton and lowest in coconut
```



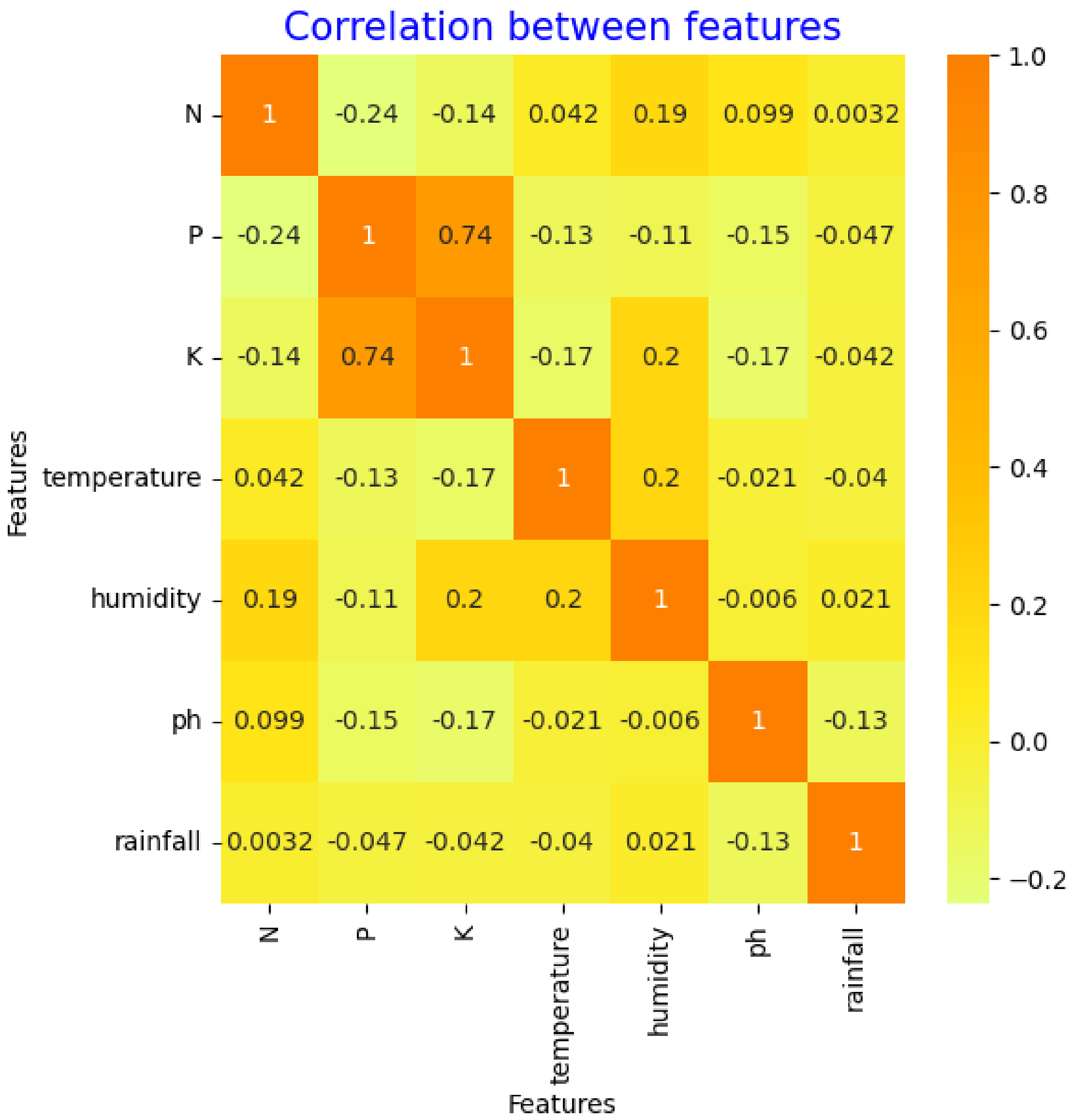
In [34]:
```
fig1=px.bar(crop_summary_new,x='label',y='K')
fig1.show()

#this shows that the crop which requires more nitrogen also requires more potassium
```

In [35]:
```
fig1=px.bar(crop_summary_new,x='label',y='P')
fig1.show()

#this shows that the crops which require more nitrogen also require more phosphorous and potassium.
```



CORRELATION

In [86]:
```
# Visualization and data exploration
fig, ax = plt.subplots(1, 1, figsize=(6, 6))

# Exclude non-numeric column before creating correlation matrix
numeric_data = data.drop('label', axis=1)
sns.heatmap(numeric_data.corr(), annot=True, cmap='Wistia')

ax.set(xlabel='Features')
ax.set(ylabel='Features')
plt.title('Correlation between features', fontsize=15, c='blue')
plt.show()
```



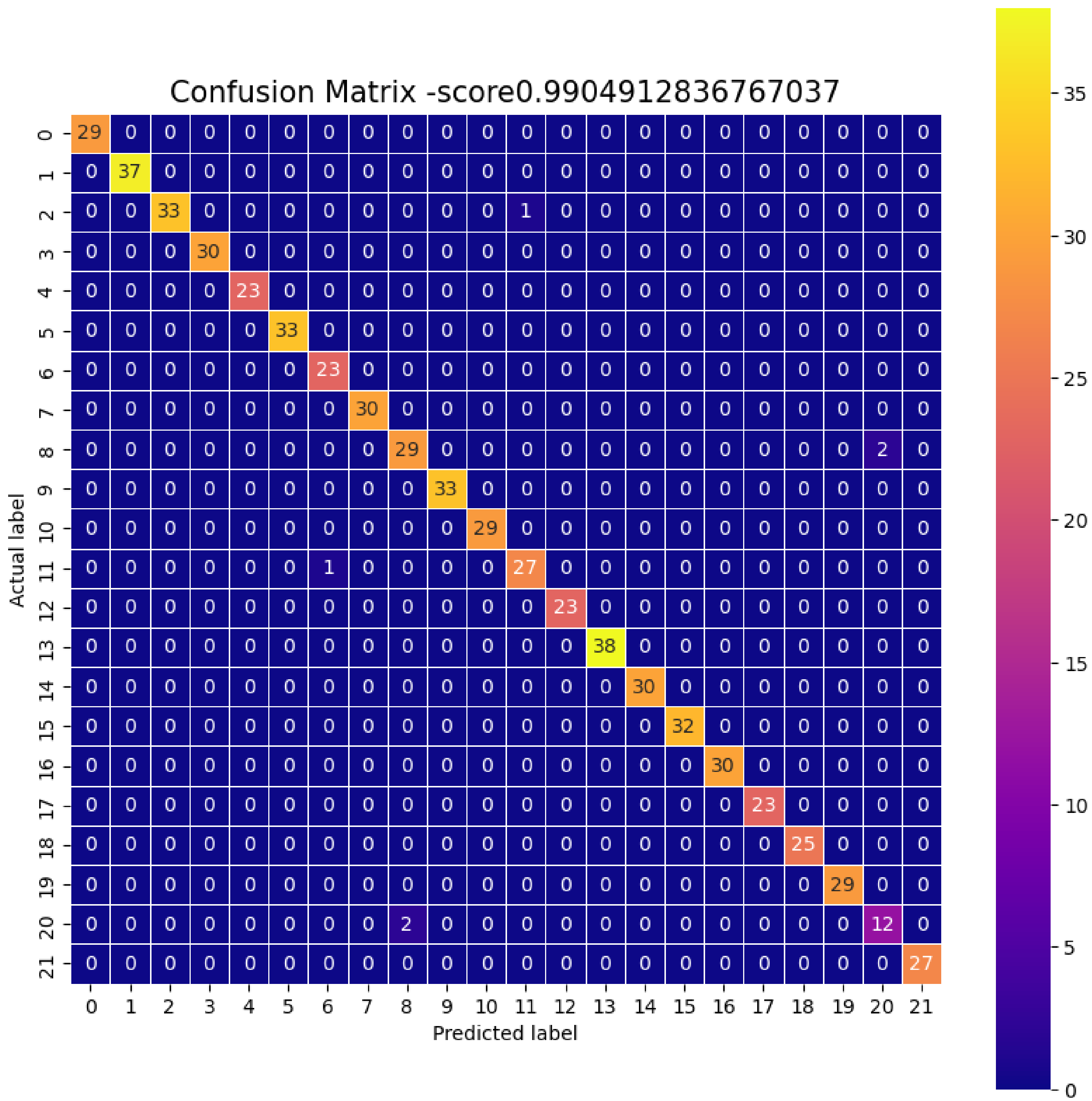
In [55]:
```
X=data.drop('label',axis=1)
y=data['label']
```

In [56]:
```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y,test_size=0.30,shuffle=True,random_state=0)
```

In [61]:
```
Classifier = DecisionTreeClassifier(criterion = 'entropy', random_state = 0)
Classifier.fit(X_train, y_train)

y_pred_decisiontree=Classifier.predict(X_test)

from sklearn.metrics import accuracy_score
accuracy=accuracy_score(y_test,y_pred_decisiontree)
print('decision tree model accuracy score: {0:0.4f}'.format(accuracy_score(y_test,y_pred_decisiontree)))

#classification report
from sklearn.metrics import classification_report
print(classification_report(y_test, y_pred_decisiontree))

from sklearn.metrics import confusion_matrix
cm = confusion_matrix(y_test, y_pred_decisiontree)

plt.figure(figsize=(10,10))
sns.heatmap(cm, annot=True, fmt=".0f", linewidths=.5, square = True, cmap = 'plasma');
plt.ylabel('Actual label');
plt.xlabel('Predicted label');
all_sample_title='Confusion Matrix -score'+str(accuracy_score(y_test, y_pred_decisiontree))
```

```
plt.title(all_sample_title, size = 15);
plt.show()

#decision tree is used to predict the yield of the crops based on the input given by the user like the nitrogen content,phosphorous content,potassium content,temperature,humidity,rainfall and ph of the wat
```

```
decision tree model accuracy score: 0.9905
              precision    recall  f1-score   support

       apple       1.00      1.00      1.00        29
      banana       1.00      1.00      1.00        37
   blackgram       1.00      0.97      0.99        34
    chickpea       1.00      1.00      1.00        30
     coconut       1.00      1.00      1.00        23
      coffee       1.00      1.00      1.00        33
      cotton       0.96      1.00      0.98        23
      grapes       1.00      1.00      1.00        30
        jute       0.94      0.94      0.94        31
 kidneybeans       1.00      1.00      1.00        33
      lentil       1.00      1.00      1.00        29
       maize       0.96      0.96      0.96        28
       mango       1.00      1.00      1.00        23
   mothbeans       1.00      1.00      1.00        38
    mungbean       1.00      1.00      1.00        30
   muskmelon       1.00      1.00      1.00        32
      orange       1.00      1.00      1.00        30
      papaya       1.00      1.00      1.00        23
  pigeonpeas       1.00      1.00      1.00        25
 pomegranate       1.00      1.00      1.00        29
        rice       0.86      0.86      0.86        14
  watermelon       1.00      1.00      1.00        27

    accuracy                           0.99       631
   macro avg       0.99      0.99      0.99       631
weighted avg       0.99      0.99      0.99       631
```

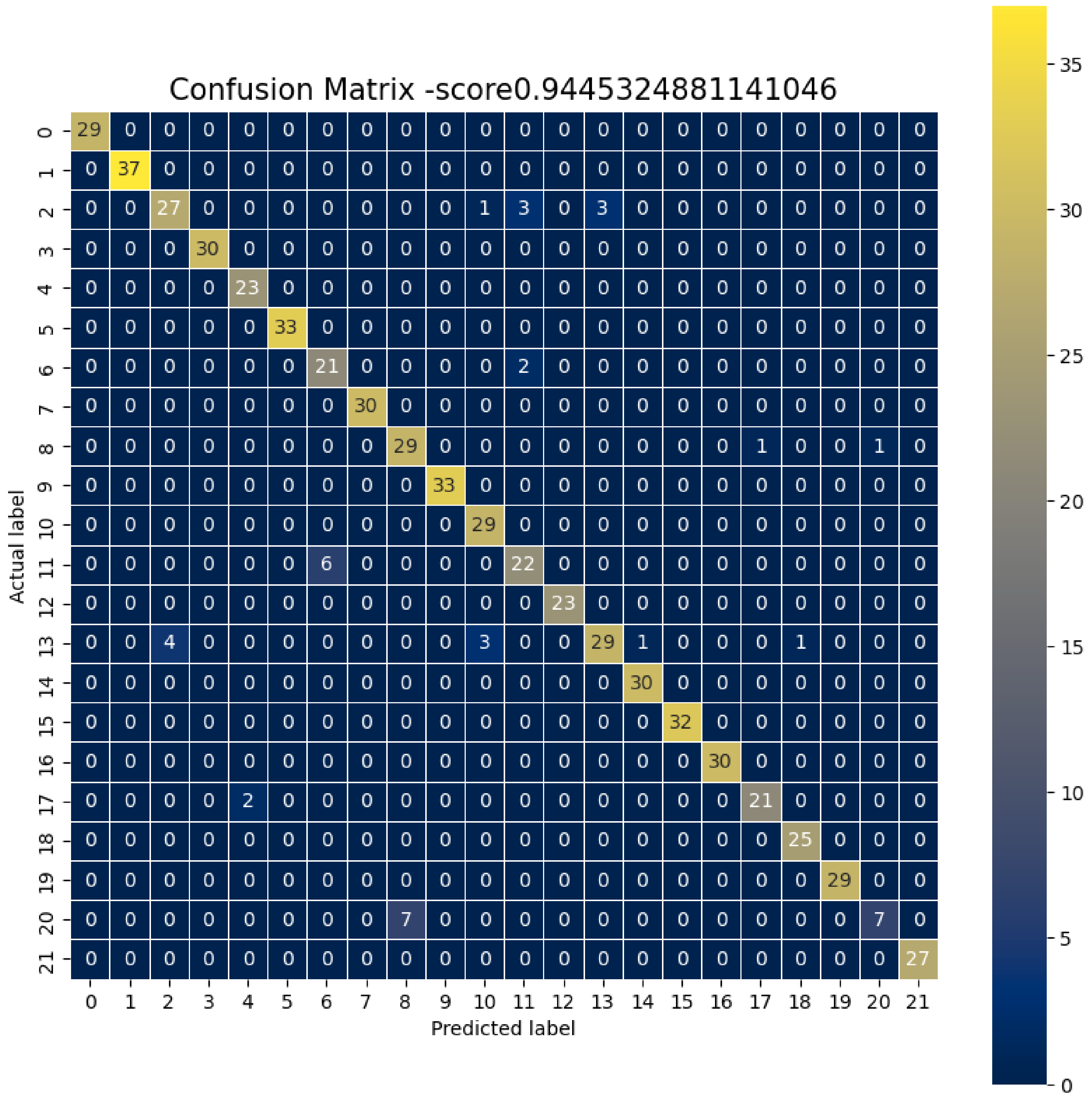


In [59]:

```
classifier_lr = LogisticRegression(random_state = 0)
classifier_lr.fit(X_train, y_train)

y_pred_lr=classifier_lr.predict(X_test)

from sklearn.metrics import accuracy_score
accuracy= accuracy_score(y_test, y_pred_lr)
print('Logistic Regression Model accuracy score: {0:0.4f}'.format(accuracy_score(y_test, y_pred_lr)))

from sklearn.metrics import classification_report
print(classification_report(y_test, y_pred_lr))

from sklearn.metrics import confusion_matrix
cm = confusion_matrix(y_test, y_pred_lr)

plt.figure(figsize=(10,10))
sns.heatmap(cm, annot=True, fmt=".0f", linewidths=.5, square = True, cmap = 'civi');
```

```
plt.ylabel('Actual label');
plt.xlabel('Predicted label');
all_sample_title='Confusion Matrix -score'+str(accuracy_score(y_test, y_pred_lr))
plt.title(all_sample_title, size = 15);
plt.show()
```

```
Logistic Regression Model accuracy score: 0.9445
              precision    recall  f1-score   support

       apple       1.00      1.00      1.00        29
      banana       1.00      1.00      1.00        37
   blackgram       0.87      0.79      0.83        34
    chickpea       1.00      1.00      1.00        30
     coconut       0.92      1.00      0.96        23
      coffee       1.00      1.00      1.00        33
      cotton       0.78      0.91      0.84        23
      grapes       1.00      1.00      1.00        30
        jute       0.81      0.94      0.87        31
 kidneybeans       1.00      1.00      1.00        33
      lentil       0.88      1.00      0.94        29
       maize       0.81      0.79      0.80        28
       mango       1.00      1.00      1.00        23
   mothbeans       0.91      0.76      0.83        38
    mungbean       0.97      1.00      0.98        30
   muskmelon       1.00      1.00      1.00        32
      orange       1.00      1.00      1.00        30
      papaya       0.95      0.91      0.93        23
  pigeonpeas       0.96      1.00      0.98        25
 pomegranate       1.00      1.00      1.00        29
        rice       0.88      0.50      0.64        14
  watermelon       1.00      1.00      1.00        27

    accuracy                           0.94       631
   macro avg       0.94      0.94      0.94       631
weighted avg       0.95      0.94      0.94       631
```

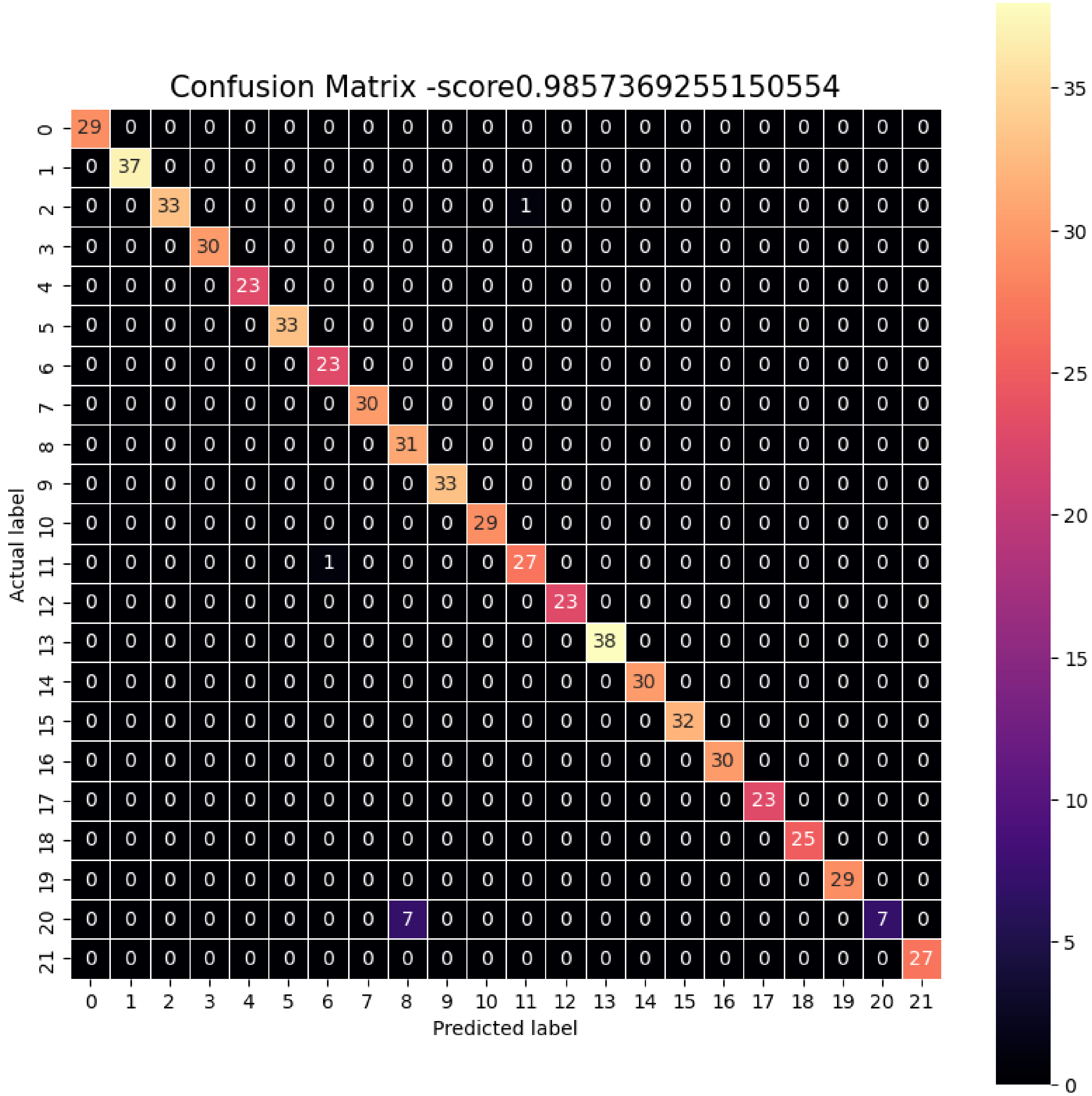


In [62]:

```
#random forest model
classifier_rf = RandomForestClassifier(n_estimators = 10, criterion = 'entropy', random_state = 0)
classifier_rf.fit(X_train, y_train)

y_pred_rf=classifier_rf.predict(X_test)

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

from sklearn.metrics import classification_report
print(classification_report(y_test, y_pred_rf))

from sklearn.metrics import confusion_matrix
cm = confusion_matrix(y_test, y_pred_rf)

plt.figure(figsize=(10,10))
```

```python
sns.heatmap(cm, annot=True, fmt=".0f", linewidths=.5, square = True, cmap = 'magma');
plt.ylabel('Actual label');
plt.xlabel('Predicted label');
all_sample_title='Confusion Matrix -score'+str(accuracy_score(y_test, y_pred_rf))
plt.title(all_sample_title, size = 15);
plt.show()
```

```
Random Forest Model accuracy score: 0.9857
              precision    recall  f1-score   support

       apple       1.00      1.00      1.00        29
      banana       1.00      1.00      1.00        37
   blackgram       1.00      0.97      0.99        34
    chickpea       1.00      1.00      1.00        30
     coconut       1.00      1.00      1.00        23
      coffee       1.00      1.00      1.00        33
      cotton       0.96      1.00      0.98        23
      grapes       1.00      1.00      1.00        30
        jute       0.82      1.00      0.90        31
 kidneybeans       1.00      1.00      1.00        33
      lentil       1.00      1.00      1.00        29
       maize       0.96      0.96      0.96        28
       mango       1.00      1.00      1.00        23
   mothbeans       1.00      1.00      1.00        38
    mungbean       1.00      1.00      1.00        30
   muskmelon       1.00      1.00      1.00        32
      orange       1.00      1.00      1.00        30
      papaya       1.00      1.00      1.00        23
  pigeonpeas       1.00      1.00      1.00        25
 pomegranate       1.00      1.00      1.00        29
        rice       1.00      0.50      0.67        14
  watermelon       1.00      1.00      1.00        27

    accuracy                           0.99       631
   macro avg       0.99      0.97      0.98       631
weighted avg       0.99      0.99      0.98       631
```

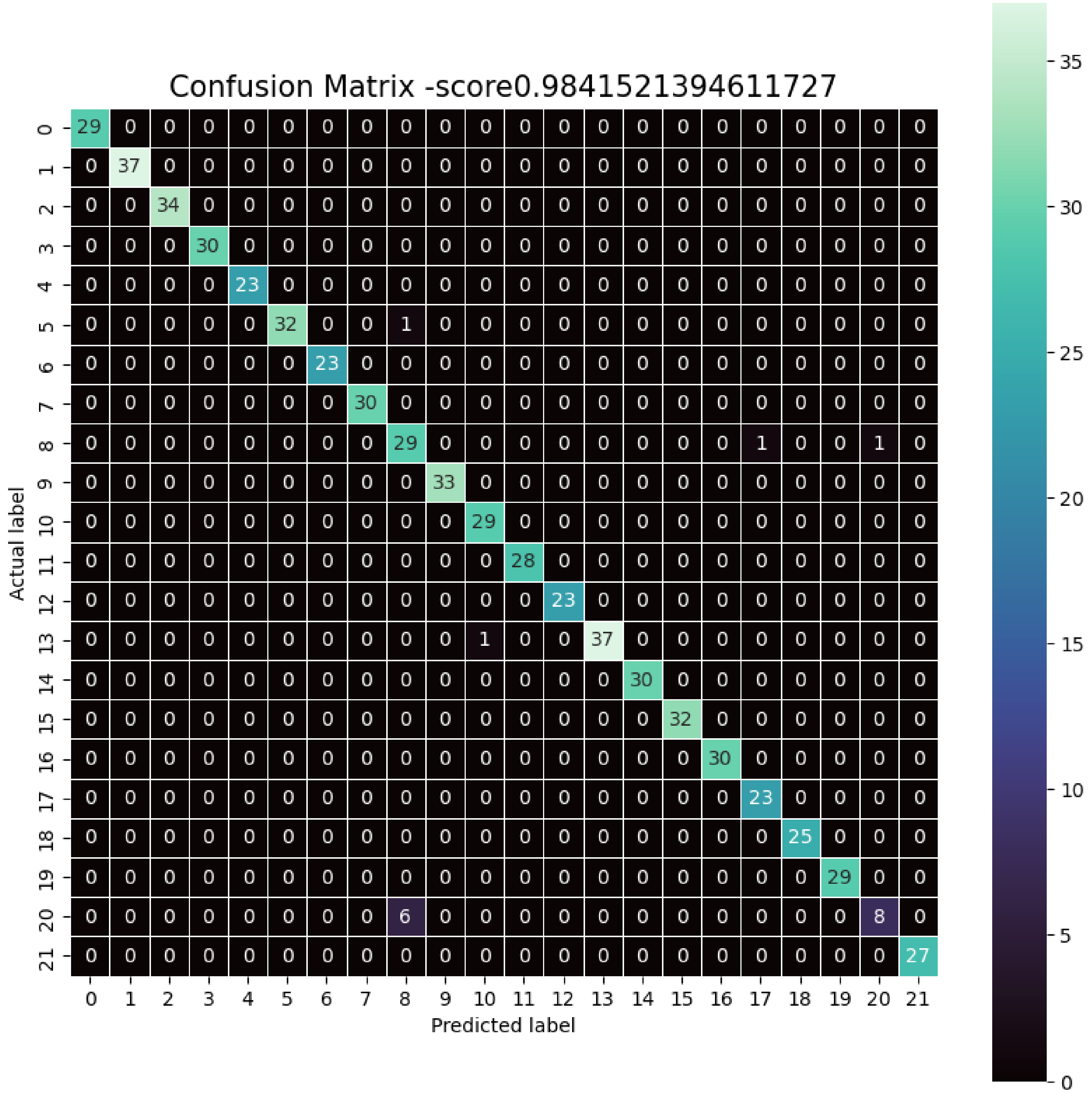


In [63]:

```
#svm model
classifier_svm = SVC(kernel = 'linear', random_state = 0)
classifier_svm.fit(X_train, y_train)

y_pred_svm=classifier_svm.predict(X_test)

from sklearn.metrics import accuracy_score
accuracy= accuracy_score(y_test, y_pred_svm)
print('SVM Model accuracy score: {0:0.4f}'.format(accuracy_score(y_test, y_pred_svm)))

from sklearn.metrics import classification_report
print(classification_report(y_test, y_pred_svm))

from sklearn.metrics import confusion_matrix
cm = confusion_matrix(y_test, y_pred_svm)

plt.figure(figsize=(10,10))
```

```python
sns.heatmap(cm, annot=True, fmt=".0f", linewidths=.5, square = True, cmap = 'mako');
plt.ylabel('Actual label');
plt.xlabel('Predicted label');
all_sample_title='Confusion Matrix -score'+str(accuracy_score(y_test, y_pred_svm))
plt.title(all_sample_title, size = 15);
plt.show()
```

```
SVM Model accuracy score: 0.9842
              precision    recall  f1-score   support

       apple       1.00      1.00      1.00        29
      banana       1.00      1.00      1.00        37
   blackgram       1.00      1.00      1.00        34
    chickpea       1.00      1.00      1.00        30
     coconut       1.00      1.00      1.00        23
      coffee       1.00      0.97      0.98        33
      cotton       1.00      1.00      1.00        23
      grapes       1.00      1.00      1.00        30
        jute       0.81      0.94      0.87        31
 kidneybeans       1.00      1.00      1.00        33
      lentil       0.97      1.00      0.98        29
       maize       1.00      1.00      1.00        28
       mango       1.00      1.00      1.00        23
   mothbeans       1.00      0.97      0.99        38
    mungbean       1.00      1.00      1.00        30
   muskmelon       1.00      1.00      1.00        32
      orange       1.00      1.00      1.00        30
      papaya       0.96      1.00      0.98        23
  pigeonpeas       1.00      1.00      1.00        25
 pomegranate       1.00      1.00      1.00        29
        rice       0.89      0.57      0.70        14
  watermelon       1.00      1.00      1.00        27

    accuracy                           0.98       631
   macro avg       0.98      0.98      0.98       631
weighted avg       0.98      0.98      0.98       631
```

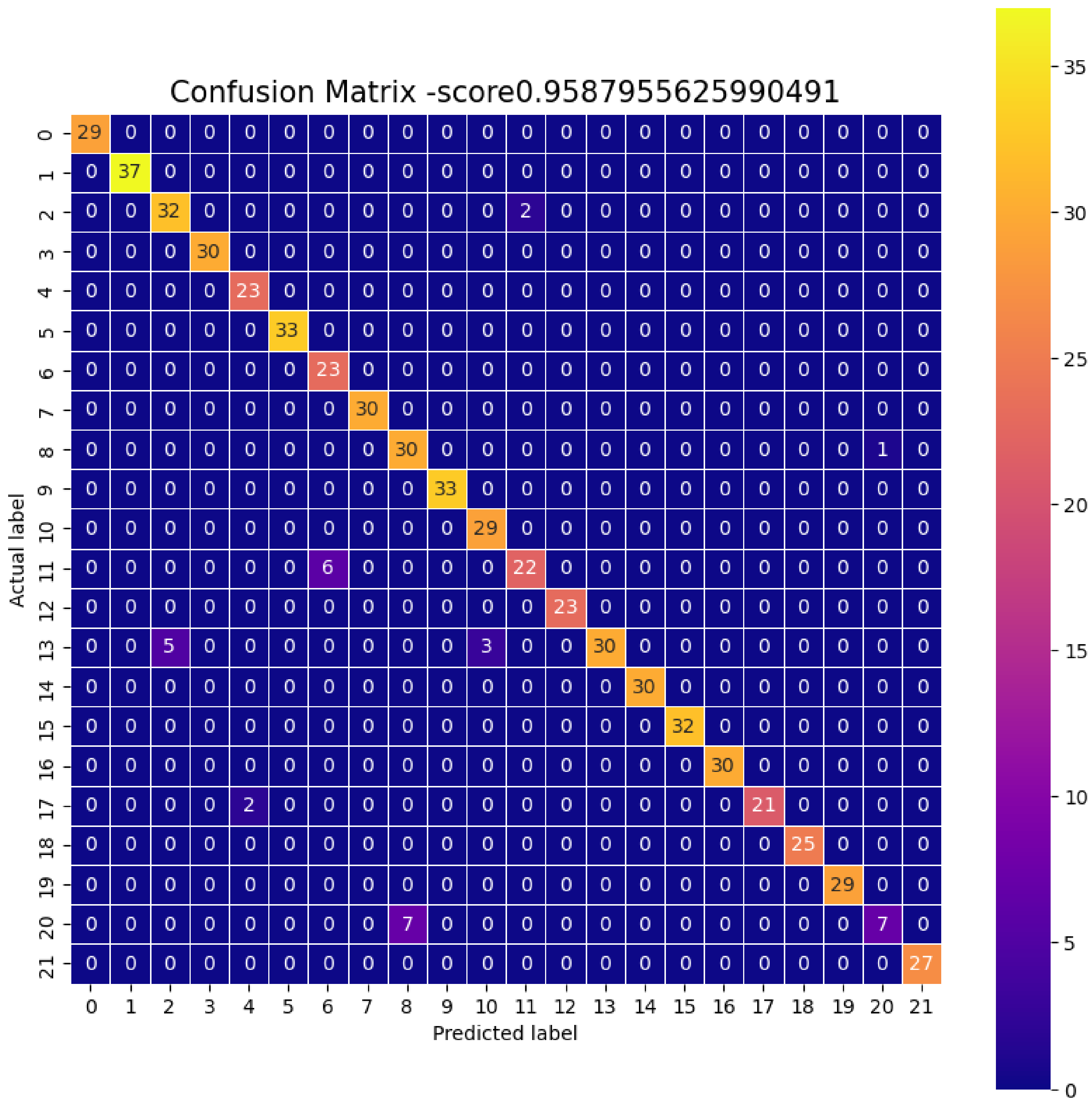


In [64]:

```
#Designing a hybrid model using LR and decision tree classifier
# Create sub models
estimators = []
model1 = LogisticRegression()
estimators.append(('logistic', model1))
model2 = DecisionTreeClassifier()
estimators.append(('cart', model2))

# Create the ensemble model
ensemble = VotingClassifier(estimators)
ensemble.fit(X_train, y_train)
y_pred_hybrid = ensemble.predict(X_test)
print("Accuracy score of ensemble model is:",accuracy_score(y_test, y_pred_hybrid))

#classification report
from sklearn.metrics import classification_report
print(classification_report(y_test, y_pred_hybrid))
```

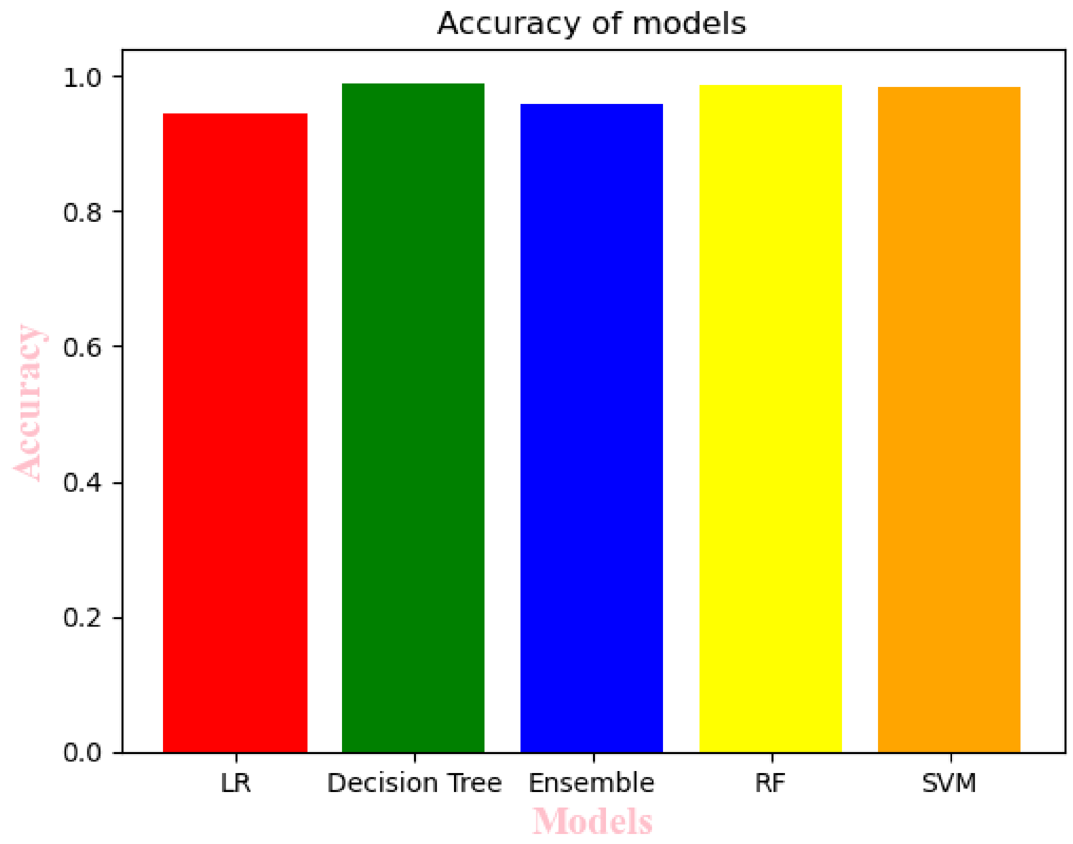
```python
from sklearn.metrics import confusion_matrix
cm = confusion_matrix(y_test, y_pred_hybrid)

plt.figure(figsize=(10,10))
sns.heatmap(cm, annot=True, fmt=".0f", linewidths=.5, square = True, cmap = 'plasma');
plt.ylabel('Actual label');
plt.xlabel('Predicted label');
all_sample_title='Confusion Matrix -score'+str(accuracy_score(y_test, y_pred_hybrid))
plt.title(all_sample_title, size = 15);
plt.show()
```

```
Accuracy score of ensemble model is: 0.9587955625990491
              precision    recall  f1-score   support

       apple       1.00      1.00      1.00        29
      banana       1.00      1.00      1.00        37
   blackgram       0.86      0.94      0.90        34
    chickpea       1.00      1.00      1.00        30
     coconut       0.92      1.00      0.96        23
      coffee       1.00      1.00      1.00        33
      cotton       0.79      1.00      0.88        23
      grapes       1.00      1.00      1.00        30
        jute       0.81      0.97      0.88        31
 kidneybeans       1.00      1.00      1.00        33
      lentil       0.91      1.00      0.95        29
       maize       0.92      0.79      0.85        28
       mango       1.00      1.00      1.00        23
   mothbeans       1.00      0.79      0.88        38
    mungbean       1.00      1.00      1.00        30
   muskmelon       1.00      1.00      1.00        32
      orange       1.00      1.00      1.00        30
      papaya       1.00      0.91      0.95        23
  pigeonpeas       1.00      1.00      1.00        25
 pomegranate       1.00      1.00      1.00        29
        rice       0.88      0.50      0.64        14
  watermelon       1.00      1.00      1.00        27

    accuracy                           0.96       631
   macro avg       0.96      0.95      0.95       631
weighted avg       0.96      0.96      0.96       631
```



All models are used for the prediction of the values of the dataset , such as

In [65]:
```python
#now design bar plot for accuracy score of models used above
models = ['LR', 'Decision Tree', 'Ensemble','RF','SVM']
accuracy = [accuracy_score(y_test, y_pred_lr),accuracy_score(y_test, y_pred_decisiontree),accuracy_score(y_test, y_pred_hybrid),accuracy_score(y_test, y_pred_rf),accuracy_score(y_test, y_pred_svm)]

#make different color for each model
colors = ['red', 'green', 'blue', 'yellow','orange']
plt.bar(models,accuracy,color=colors)
plt.xlabel('Models',color='pink',fontsize=15,fontweight='bold',horizontalalignment='center',fontname='Times New Roman')
plt.ylabel('Accuracy',color='pink',fontsize=15,fontweight='bold',horizontalalignment='center',fontname='Times New Roman')
plt.title('Accuracy of models')
plt.show()
```



In [66]:
```
X_test[0:1]
```

Out[66]:

	N	P	K	temperature	humidity	ph	rainfall
1203	36	125	196	37.465668	80.659687	6.155261	66.838723

In [67]:
```
result=Classifier.predict(X_test[0:1])
```

In [68]:
```
result
```

Out[68]:
```
array(['grapes'], dtype=object)
```

In [69]:
```
y_test[0:1]
```

Out[69]:
```
1203    grapes
Name: label, dtype: object
```

In [ ]:

THANK YOU

In [ ]: