```
import pandas as pd
import numpy as np
import plotly.graph_objs as go
import plotly.express as px
import seaborn as sns
import matplotlib.pyplot as plt
import random
from plotly.subplots import make_subplots
from sklearn.model_selection import train_test_split
from sklearn.linear_model import RidgeClassifier
from sklearn.naive_bayes import GaussianNB
from sklearn import tree
from sklearn.metrics import accuracy_score
from sklearn.metrics import confusion_matrix
from sklearn.datasets import make_classification
from matplotlib import pyplot
from sklearn.model_selection import learning_curve
from sklearn.model_selection import ShuffleSplit
from sklearn.metrics import r2_score
from sklearn.preprocessing import StandardScaler



def plot_learning_curve(estimator, title, X, y, ylim=None, cv=None,
                        n_jobs=1, train_sizes=np.linspace(.1, 1.0, 5)):

    plt.figure()
    plt.title(title)
    if ylim is not None:
        plt.ylim(*ylim)
    plt.xlabel("Training examples")
    plt.ylabel("Score")
    train_sizes, train_scores, test_scores = learning_curve(
        estimator, X, y, cv=cv, n_jobs=n_jobs, train_sizes=train_sizes)
    train_scores_mean = np.mean(train_scores, axis=1)
    train_scores_std = np.std(train_scores, axis=1)
    test_scores_mean = np.mean(test_scores, axis=1)
    test_scores_std = np.std(test_scores, axis=1)
    plt.grid()

    plt.fill_between(train_sizes, train_scores_mean - train_scores_std,
                     train_scores_mean + train_scores_std, alpha=0.1,
                     color="r")
    plt.fill_between(train_sizes, test_scores_mean - test_scores_std,
                     test_scores_mean + test_scores_std, alpha=0.1,
                     color="g")
    plt.plot(train_sizes, train_scores_mean, 'o-', color="r",
             label="Training score")
    plt.plot(train_sizes, test_scores_mean, 'o-', color="g",
             label="Cross-validation score")

    plt.legend(loc="best")
    return plt


colorarr = ['#0592D0','#Cd7f32', '#E97451', '#Bdb76b', '#954535', '#C2b280', '#808000','#C2b280', '#E4d008', '#9acd32', '#Eedc82', '#E4d96f',
           '#32cd32','#39ff14','#00ff7f', '#008080', '#36454f', '#F88379', '#Ff4500', '#Ffb347', '#A94064', '#E75480', '#Ffb6c1', '#E5e4e2',
           '#Faf0e6', '#8c92ac', '#Dbd7d2','#A7a6ba', '#B38b6d']

url = 'https://raw.githubusercontent.com/Istiak-Mahmud/CropsPred-Meta-model/main/Final_Crops_recommendation_Dataset.csv'
df = pd.read_csv(url)
df.head()
```

	N	P	K	temperature	humidity	ph	label
0	93	56	42	23.85754	82.25573	7.385763	Paddy
1	79	43	39	21.66628	80.70961	7.062779	Paddy
2	95	52	36	26.22917	83.83626	5.543360	Paddy
3	67	58	39	25.28272	80.54373	5.453592	Paddy
4	70	36	42	21.84107	80.72886	6.946210	Paddy

```
df.shape
```

```
(3000, 7)
```

```
df.columns
```

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

```
df.isnull().any()
```

```
N              False
P              False
K              False
temperature    False
humidity       False
ph             False
label          False
dtype: bool
```

```
print("Number of various crops: ", len(df['label'].unique()))
print("List of crops: ", df['label'].unique())
```

```
Number of various crops:  30
List of crops:  ['Paddy' 'Wheat' 'Potato' 'Tomato' 'Tea' 'mango' 'mungbean' 'jute'
 'lentil' 'maize' 'apple' 'mothbeans' 'banana' 'cotton' 'coffee'
 'watermelon' 'coconut' 'grapes' 'chickpea' 'muskmelon' 'Pumpkin'
 'blackgram' 'pigeonpeas' 'orange' 'Pulses' 'kidneybeans' 'pomegranate'
 'papaya' 'Onion' 'Ginger']
```

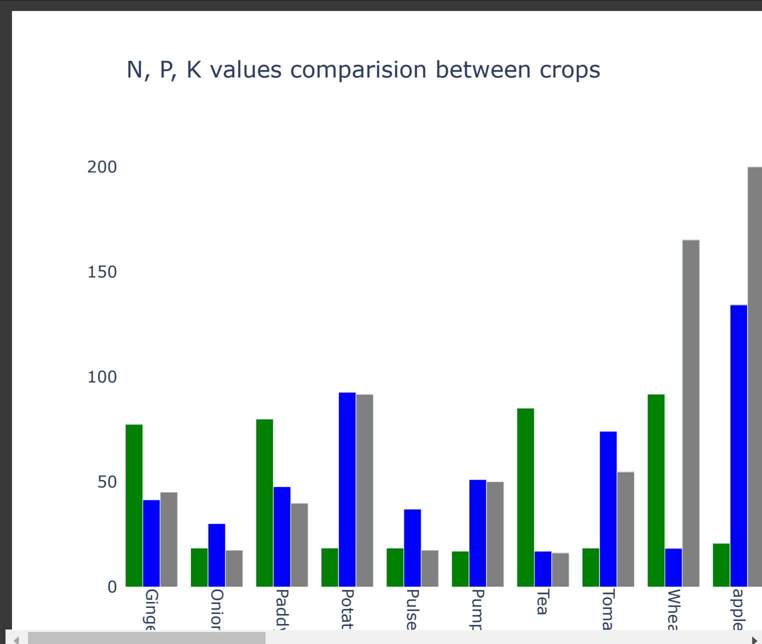
```
df['label'].value_counts()
```

```
Paddy          100
Wheat          100
Onion          100
papaya         100
pomegranate    100
kidneybeans    100
Pulses         100
orange         100
pigeonpeas     100
blackgram      100
Pumpkin        100
muskmelon      100
chickpea       100
grapes         100
coconut        100
watermelon     100
coffee         100
cotton         100
banana         100
mothbeans      100
apple          100
maize          100
lentil         100
jute           100
mungbean       100
mango          100
Tea            100
Tomato         100
Potato         100
Ginger         100
Name: label, dtype: int64
```

```
crop_summary = pd.pivot_table(df,index=['label'],aggfunc='mean')
crop_summary.head()
```

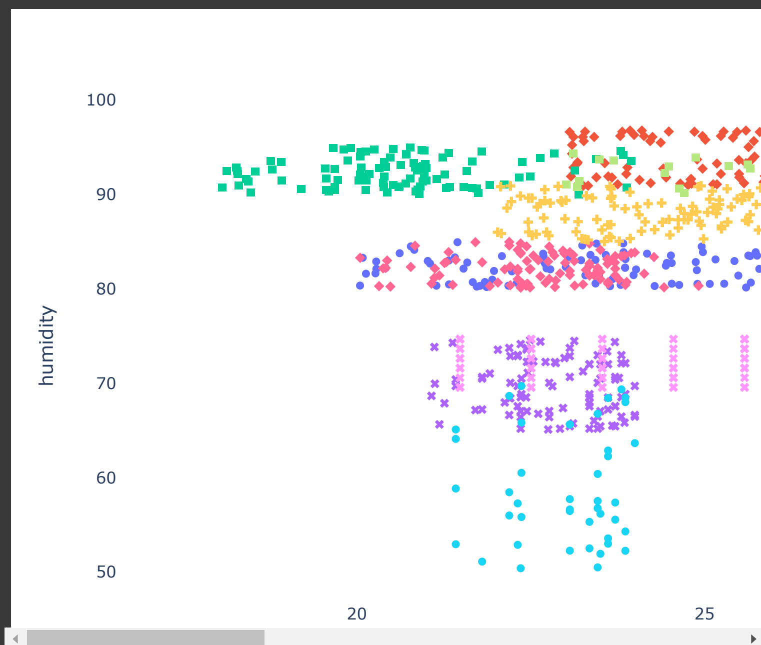
label	K	N	P	humidity	ph	temperature
Ginger	45.15	77.40	41.48	88.005019	5.913478	24.055585
Onion	17.52	18.52	30.16	72.121500	6.999718	23.518770
Paddy	39.86	79.92	47.72	82.275352	6.434299	23.719110
Potato	91.65	18.53	92.65	92.336767	6.293546	20.609111
Pulses	17.52	18.52	37.04	82.222873	5.523819	22.660551

```
fig = go.Figure()
fig.add_trace(go.Bar(
    x=crop_summary.index,
    y=crop_summary['N'],
    name='Nitrogen',
    marker_color='Green'
))
fig.add_trace(go.Bar(
    x=crop_summary.index,
    y=crop_summary['P'],
    name='Phosphorous',
    marker_color='Blue'
))
fig.add_trace(go.Bar(
    x=crop_summary.index,
    y=crop_summary['K'],
    name='Potash',
    marker_color='Gray'
))

fig.update_layout(title="N, P, K values comparision between crops",
                  plot_bgcolor='white',
                  barmode='group',
                  xaxis_tickangle=90)

fig.show()
```



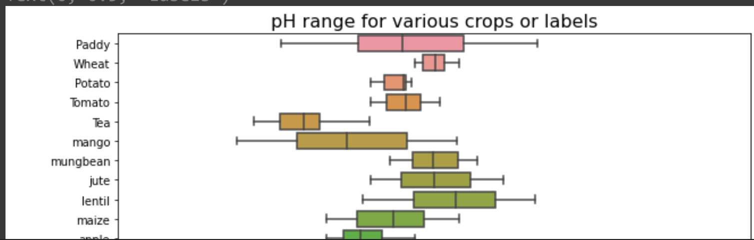

```
crop_scatter = df[(df['label']=='Paddy') |
                  (df['label']=='Wheat') |
                  (df['label']=='Onion') |
                  (df['label']=='papaya') |
                  (df['label']=='Pomegranate') |
                  (df['label']=='Kidneybeans') |
                  (df['label']=='Pulses') |
                  (df['label']=='Orange')|
                  (df['label']=='Pigeonpeas')|
                  (df['label']=='Blackgram')|
                  (df['label']=='Pumpkin')|
                  (df['label']=='Muskmelon')|
                  (df['label']=='Chickpea')|
                  (df['label']=='Grapes')|
                  (df['label']=='Coconut')|
                  (df['label']=='Watermelon')|
                  (df['label']=='Coffee')|
                  (df['label']=='Cotton')|
                  (df['label']=='Banana')|
                  (df['label']=='Mothbeans')|
```

```
                  (df['label']=='Apple')|
                  (df['label']=='Maize')|
                  (df['label']=='Lentil')|
                  (df['label']=='Jute')|
                  (df['label']=='Mugbean')|
                  (df['label']=='Mango')|
                  (df['label']=='Tea')|
                  (df['label']=='Tomato')|
                  (df['label']=='Potato')|
                  (df['label']=='Ginger')]

fig = px.scatter(crop_scatter, x="temperature", y="humidity", color="label", symbol="label")
fig.update_layout(plot_bgcolor='white')
fig.update_xaxes(showgrid=False)
fig.update_yaxes(showgrid=False)

fig.show()
```



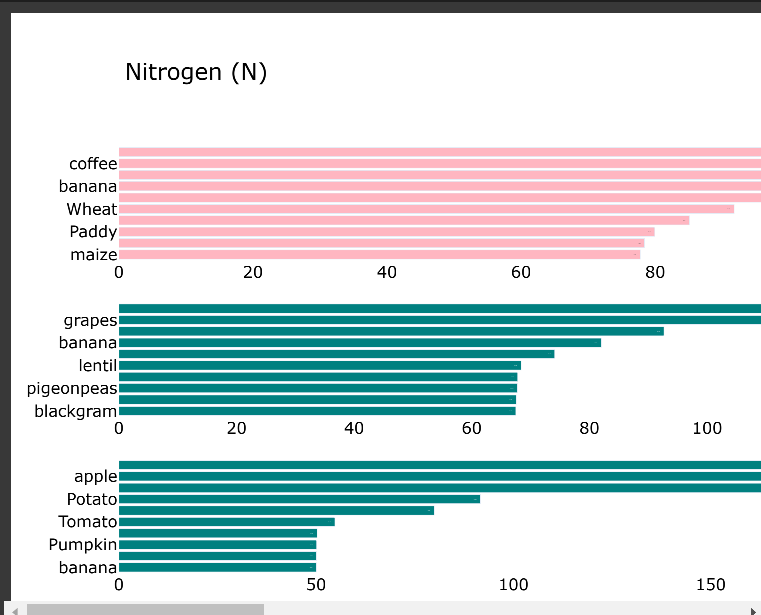

```
fig, ax = plt.subplots(figsize=(10, 9.5))

boxplot=sns.boxplot(y='label',x='ph',data=df, ax=ax)
sns.set_context("paper", font_scale=0.9)
boxplot.axes.set_title("pH range for various crops or labels", fontsize=16)
boxplot.set_xlabel("pH", fontsize=14)
boxplot.set_ylabel("Labels", fontsize=14)
```

```
Text(0, 0.5, 'Labels')
```




```
crop_summary_N = crop_summary.sort_values(by='N', ascending=False)
crop_summary_P = crop_summary.sort_values(by='P', ascending=False)
crop_summary_K = crop_summary.sort_values(by='K', ascending=False)

fig = make_subplots(rows=3, cols=2)

top_N = {
    'y' : crop_summary_N['N'][0:10].sort_values().index,
    'x' : crop_summary_N['N'][0:10].sort_values()
}

last_N = {
    'y' : crop_summary_N['N'][-10:].index,
    'x' : crop_summary_N['N'][-10:]
}

top_P = {
    'y' : crop_summary_P['P'][0:10].sort_values().index,
    'x' : crop_summary_P['P'][0:10].sort_values()
}

last_P = {
    'y' : crop_summary_P['P'][-10:].index,
    'x' : crop_summary_P['P'][-10:]
}

top_K = {
    'y' : crop_summary_K['K'][0:10].sort_values().index,
    'x' : crop_summary_K['K'][0:10].sort_values()
}

last_K = {
    'y' : crop_summary_K['K'][-10:].index,
    'x' : crop_summary_K['K'][-10:]
}

fig.add_trace(
    go.Bar(top_N,
           name="Most nitrogen required",
           marker_color=random.choice(colorarr),
           orientation='h',
          text=top_N['x']),

    row=1, col=1
)

fig.add_trace(
    go.Bar(last_N,
           name="Least nitrogen required",
           marker_color=random.choice(colorarr),
           orientation='h',
          text=last_N['x']),
    row=1, col=2
)

fig.add_trace(
    go.Bar(top_P,
           name="Most phosphorus required",
           marker_color=random.choice(colorarr),
           orientation='h',
          text=top_P['x']),

    row=2, col=1
)

fig.add_trace(
```

```
    go.Bar(last_P,
           name="Least phosphorus required",
           marker_color=random.choice(colorarr),
           orientation='h',
          text=last_P['x']),
    row=2, col=2
)

fig.add_trace(
    go.Bar(top_K,
           name="Most potassium required",
           marker_color=random.choice(colorarr),
           orientation='h',
          text=top_K['x']),

    row=3, col=1
)

fig.add_trace(
    go.Bar(last_K,
           name="Least potassium required",
           marker_color=random.choice(colorarr),
           orientation='h',
          text=last_K['x']),
    row=3, col=2
)

fig.update_traces(texttemplate='%{text}', textposition='inside')
fig.update_layout(title_text="Nitrogen (N)",
                  plot_bgcolor='white',
                  font_size=12,
                  font_color='black',
                 height=500)

fig.update_xaxes(showgrid=False)
fig.update_yaxes(showgrid=False)
fig.show()
```




```
X = df.drop(columns=['label'])
y = df['label']

X_train,X_test,y_train,y_test = train_test_split(X,y,test_size=0.2,random_state=8)
print(X_train.shape)
```

```
(2400, 6)
```

```
#  from sklearn.linear_model import RidgeClassifier
# from sklearn import svm
# from sklearn.linear_model import SGDClassifier
```

```
# from sklearn.neighbors import KNeighborsClassifier
# from sklearn.gaussian_process import GaussianProcessClassifier
#  from sklearn.naive_bayes import GaussianNB
#  from sklearn import tree
# import lightgbm as lgb

# models = []
# models.append(('LGBM',lgb.LGBMClassifier()))
# models.append(('Ridge', RidgeClassifier()))
# models.append(('SVR', svm.SVC()))
# models.append(('SGDC', SGDClassifier()))
# models.append(('KNN', KNeighborsClassifier(n_neighbors=3)))
# models.append(('GPC', GaussianProcessClassifier()))
# models.append(('BaysNa', GaussianNB()))
# models.append(('Tree', tree.DecisionTreeClassifier()))

# results = []
# names = []
# scoring = 'accuracy'
# for name, model in models:
#   Y_pred = model.fit(X_train, y_train).predict(X_test)
#   print(name)
#   print('Accuracy score: %.2f'
#         % accuracy_score(y_test, Y_pred))
```

```
#from sklearn.ensemble import KNeighborsClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import GradientBoostingClassifier
```

```
estimators = [
    ('Ridge', RandomForestClassifier(n_estimators=10, random_state=42)),
    ('BaysNa', GaussianNB()),
    ('Tree', tree.DecisionTreeClassifier())
]
```

```
from sklearn.ensemble import StackingClassifier

clf = StackingClassifier(
    estimators=estimators,
    #final_estimator=SGDClassifier(),
    #final_estimator=LogisticRegression(),
    final_estimator=KNeighborsClassifier(n_neighbors=7),
    #final_estimator=lgb.LGBMClassifier(),
    cv=5
)
```

```
clf.fit(X_train, y_train)
```

```
StackingClassifier(cv=5,
                   estimators=[('Ridge',
                                RandomForestClassifier(n_estimators=10,
                                                       random_state=42)),
                               ('BaysNa', GaussianNB()),
                               ('Tree', DecisionTreeClassifier())],
                   final_estimator=KNeighborsClassifier(n_neighbors=7))
```

```
y_pred = clf.predict(X_test)
```

```
accuracy_score(y_test,y_pred)
```

```
0.9566666666666667
```

```
print('Training set score: {:.4f}'.format(clf.score(X_train, y_train)))
print('Test set score: {:.4f}'.format(clf.score(X_test, y_test)))
```

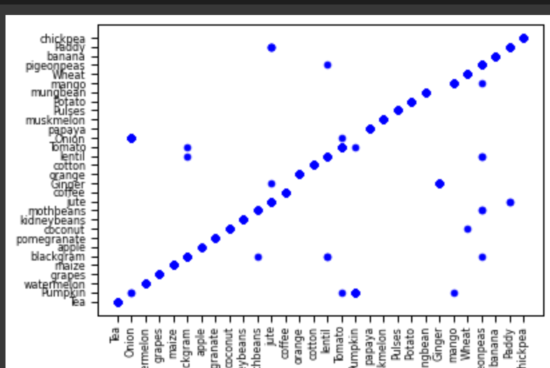
```
Training set score: 0.9942
Test set score: 0.9567
```

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

```
              precision    recall  f1-score   support

      Ginger       0.94      1.00      0.97        16
       Onion       0.96      0.93      0.94        27
       Paddy       0.80      0.89      0.84        18
      Potato       1.00      1.00      1.00        20
      Pulses       1.00      1.00      1.00        16
     Pumpkin       0.83      0.95      0.89        21
         Tea       1.00      1.00      1.00        20
      Tomato       0.92      0.92      0.92        25
       Wheat       1.00      0.95      0.98        21
       apple       1.00      1.00      1.00        11
      banana       1.00      1.00      1.00        20
   blackgram       0.84      0.91      0.87        23
    chickpea       1.00      1.00      1.00        17
     coconut       0.95      1.00      0.97        18
      coffee       1.00      1.00      1.00        24
      cotton       1.00      1.00      1.00        18
      grapes       1.00      1.00      1.00        18
        jute       0.92      0.81      0.86        27
 kidneybeans       1.00      1.00      1.00        24
      lentil       0.82      0.82      0.82        17
       maize       1.00      1.00      1.00        25
       mango       0.95      0.95      0.95        19
   mothbeans       0.87      0.93      0.90        14
    mungbean       1.00      1.00      1.00        17
   muskmelon       1.00      1.00      1.00        24
      orange       1.00      1.00      1.00        20
      papaya       1.00      1.00      1.00        19
  pigeonpeas       0.95      0.78      0.86        27
 pomegranate       1.00      1.00      1.00        15
  watermelon       1.00      1.00      1.00        19

    accuracy                           0.96       600
   macro avg       0.96      0.96      0.96       600
weighted avg       0.96      0.96      0.96       600
```

```
# newdata1=clf.predict([[90, 50, 50, 20.879744, 75, 6.5]])
# newdata1
```

```
plt.scatter(y_test,
            y_pred,
            color='blue')
plt.xticks(rotation=90)
plt.show()
```

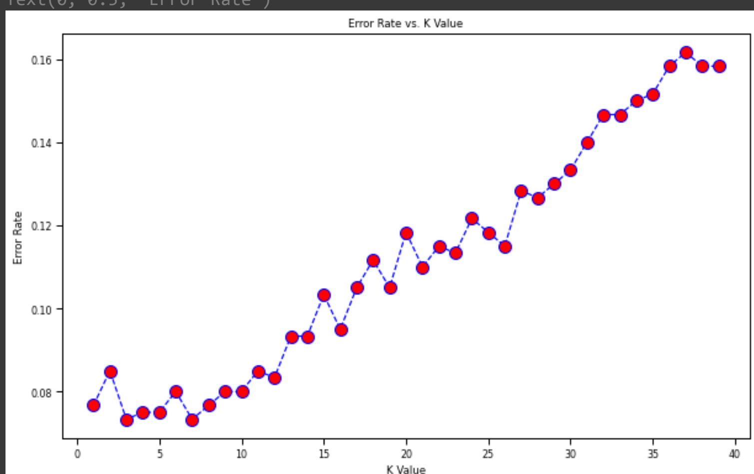



```
sns.heatmap(confusion_matrix(y_test, y_pred), annot = True)
print("Number of mislabeled points out of a total %d points : %d"
  % (X_test.shape[0], (y_test != y_pred).sum()))
```

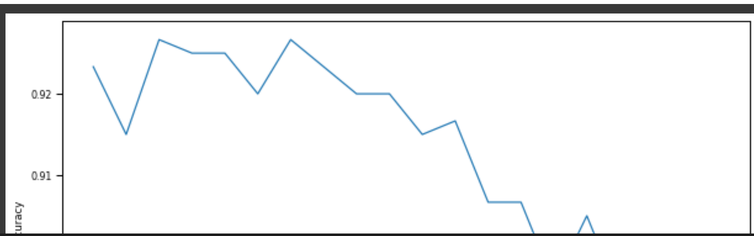
```
Number of mislabeled points out of a total 600 points : 26
```

```
error_rate = []

# Will take some time
for i in range(1,40):

    knn = KNeighborsClassifier(n_neighbors=i)
    knn.fit(X_train,y_train)
    pred_i = knn.predict(X_test)
    error_rate.append(np.mean(pred_i != y_test))


plt.figure(figsize=(10,6))
plt.plot(range(1,40),error_rate,color='blue', linestyle='dashed', marker='o',
         markerfacecolor='red', markersize=10)
plt.title('Error Rate vs. K Value')
plt.xlabel('K Value')
plt.ylabel('Error Rate')
```

```
Text(0, 0.5, 'Error Rate')
```



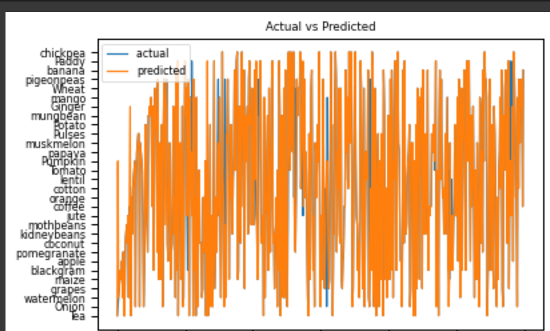

```
#Hyperparameter Tuning
from sklearn.metrics import confusion_matrix
from sklearn.metrics import classification_report
from sklearn import metrics
mean_acc = np.zeros(20)
for i in range(1,21):
    #Train Model and Predict
    knn = KNeighborsClassifier(n_neighbors = i).fit(X_train,y_train)
    yhat= knn.predict(X_test)
    mean_acc[i-1] = metrics.accuracy_score(y_test, yhat)
mean_acc

loc = np.arange(1,21,step=1.0)
plt.figure(figsize = (10, 6))
plt.plot(range(1,21), mean_acc)
plt.xticks(loc)
plt.xlabel('Number of Neighbors ')
plt.ylabel('Accuracy')
plt.show()
```




```
# evaluate knn performance on train and test sets with different numbers of neighbors

train_scores, test_scores = list(), list()
# define the tree depths to evaluate
values = [i for i in range(5, 50)]
# evaluate a decision tree for each depth
for i in values:
    # configure the model
    model = KNeighborsClassifier(n_neighbors=i)
    # fit model on the training dataset
    model.fit(X_train, y_train)
    # evaluate on the train dataset
    train_yhat = model.predict(X_train)
    train_acc = accuracy_score(y_train, train_yhat)
    train_scores.append(train_acc)
    # evaluate on the test dataset
    test_yhat = model.predict(X_test)
    test_acc = accuracy_score(y_test, test_yhat)
    test_scores.append(test_acc)
    # summarize progress
    print('>%d, train: %.3f, test: %.3f' % (i, train_acc, test_acc))
# plot of train and test scores vs number of neighbors
pyplot.plot(values, train_scores, '-o', label='Train')
pyplot.plot(values, test_scores, '-o', label='Test')
pyplot.title('Training and testing set accuracy vs. K-value')
pyplot.xlabel('K-value')
pyplot.ylabel('Accuracy')
pyplot.legend()
pyplot.show()
```

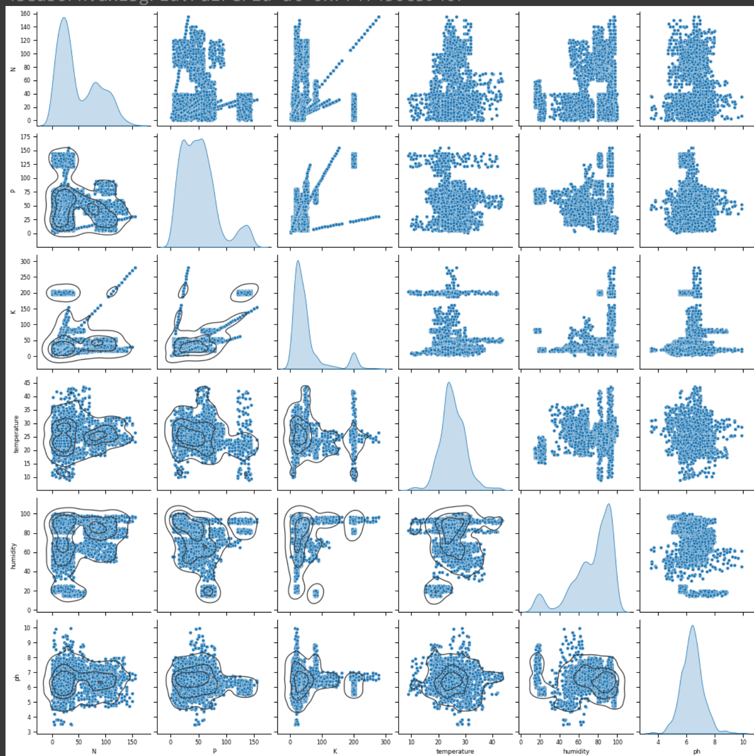
```
>5, train: 0.958, test: 0.925
>6, train: 0.948, test: 0.920
>7, train: 0.954, test: 0.927
>8, train: 0.939, test: 0.923
>9, train: 0.942, test: 0.920
>10, train: 0.935, test: 0.920
>11, train: 0.938, test: 0.915
>12, train: 0.932, test: 0.917
>13, train: 0.930, test: 0.907
>14, train: 0.925, test: 0.907
>15, train: 0.926, test: 0.897
>16, train: 0.919, test: 0.905
>17, train: 0.921, test: 0.895
>18, train: 0.918, test: 0.888
>19, train: 0.921, test: 0.895
>20, train: 0.919, test: 0.882
>21, train: 0.915, test: 0.890
>22, train: 0.907, test: 0.885
>23, train: 0.906, test: 0.887
>24, train: 0.905, test: 0.878
>25, train: 0.904, test: 0.882
>26, train: 0.902, test: 0.885
>27, train: 0.902, test: 0.872
```

```
dm = pd.DataFrame({'Actual': y_test, 'Predicted': y_pred}).reset_index()
x_axis=dm.index
y_axis=dm.Actual
y1_axis=dm.Predicted
plt.plot(x_axis,y_axis)
plt.plot(x_axis,y1_axis)
plt.title("Actual vs Predicted")
plt.legend(["actual ","predicted"])
b=plt.show()
b
```




```
g = sns.pairplot(df, diag_kind="kde")
g.map_lower(sns.kdeplot, levels=4, color=".2")
```

```
<seaborn.axisgrid.PairGrid at 0x7f4f450c3940>
```




```
correlation_mat = df.corr()
correlation_mat
plt.figure(figsize=(10,8))
#sns.color_palette("Blues", as_cmap=True)
# fig, ax = plt.subplots(figsize=(10, 8))

sns.heatmap(correlation_mat,cmap="Greens", linewidths=1,annot=True, fmt="f")
sns.set_context("paper", font_scale=1.3)
```


```
# import pickle
# with open('crop_prediction.pickle','wb') as f:
#   pickle.dump(KNeighborsClassifier,f)
```

```
# import json
# columns = {
#     'data_columns' : [col.lower() for col in X.columns]
# }
```

```
# with open("columns.json","w") as f:
#   f.write(json.dumps(columns))
```

Gaussian Naive Bayes model implementation

M. Kalimuthu, P. Vaishnavi and M. Kishore, "Crop Prediction using Machine Learning," 2020 Third International Conference on Smart Systems and Inventive Technology (ICSSIT), 2020, pp. 926-932, doi: 10.1109/ICSSIT48917.2020.9214190.

- As this paperwork have not any reference datasets.
- We did the same model using a Kaggle dataset.
- This paperwork contains four parameters - Temperature, Humidity, pH and Rainfall.

```
url1 ='https://raw.githubusercontent.com/Istiak-Mahmud/CropsPred-Meta-model/main/Crop_recommendation_Kaggle.csv'
# data = pd.read_csv(path_NB)
data = pd.read_csv(url1)
data.head()

# url = 'https://raw.githubusercontent.com/Istiak-Mahmud/CropsPred-Meta-model/main/Final_Crops_recommendation_Dataset.csv'
# df = pd.read_csv(url)
# df.head()
```

	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

```
# data = df
data.drop('N', inplace=True, axis=1)
data.drop('P', inplace=True, axis=1)
data.drop('K', inplace=True, axis=1)
data
```

	temperature	humidity	ph	rainfall	label
0	20.879744	82.002744	6.502985	202.935536	rice
1	21.770462	80.319644	7.038096	226.655537	rice
2	23.004459	82.320763	7.840207	263.964248	rice
3	26.491096	80.158363	6.980401	242.864034	rice
4	20.130175	81.604873	7.628473	262.717340	rice
...	...	...	...	...	...
2195	26.774637	66.413269	6.780064	177.774507	coffee
2196	27.417112	56.636362	6.086922	127.924610	coffee
2197	24.131797	67.225123	6.362608	173.322839	coffee
2198	26.272418	52.127394	6.758793	127.175293	coffee
2199	23.603016	60.396475	6.779833	140.937041	coffee

```
y_NB1 = data['label']
x_NB1 = data.drop(['label'],
              axis = 1)
```

```
X_train, X_test, Y_train, Y_test = train_test_split(x_NB1,
                                                    y_NB1,
                                                    test_size = 0.2,
                                                    random_state = 5)
```

```
model_NB1 = []
model_NB1.append(('BaysNa', GaussianNB()))
```

```
scoring = 'accuracy'
for name, model_NB1 in model_NB1:
  Y_pred = model_NB1.fit(X_train, Y_train).predict(X_test)
  print(name)
  print('Accuracy score: %.2f'
        % accuracy_score(Y_test, Y_pred))
```

```
BaysNa
Accuracy score: 0.95
```

```
print('Training set score: {:.4f}'.format(model_NB1.score(X_train, Y_train)))
print('Test set score: {:.4f}'.format(model_NB1.score(X_test, Y_test)))
```

```
Training set score: 0.9568
Test set score: 0.9545
```

```
from sklearn.metrics import precision_recall_fscore_support
precision_recall_fscore_support(Y_test, Y_pred, average='macro')
```

```
(0.9547069890244825, 0.9568227624976057, 0.9536147197163403, None)
```

```
from sklearn.metrics import classification_report
print(classification_report(Y_test, Y_pred))
```

```
              precision    recall  f1-score   support

       apple       0.92      0.96      0.94        24
      banana       0.94      1.00      0.97        15
   blackgram       0.96      1.00      0.98        22
    chickpea       1.00      1.00      1.00        19
     coconut       1.00      1.00      1.00        20
      coffee       0.89      0.96      0.92        25
      cotton       0.92      0.85      0.88        13
      grapes       0.89      1.00      0.94        17
        jute       0.88      1.00      0.94        15
 kidneybeans       1.00      1.00      1.00        16
      lentil       0.95      1.00      0.97        18
       maize       0.96      0.93      0.94        27
       mango       0.90      1.00      0.95        18
   mothbeans       1.00      0.91      0.95        22
    mungbean       1.00      1.00      1.00        19
   muskmelon       1.00      1.00      1.00        24
      orange       1.00      0.83      0.90        23
      papaya       0.91      1.00      0.95        20
  pigeonpeas       1.00      0.75      0.86        24
 pomegranate       0.89      0.94      0.91        17
        rice       1.00      0.93      0.97        15
  watermelon       1.00      1.00      1.00        27

    accuracy                           0.95       440
   macro avg       0.95      0.96      0.95       440
weighted avg       0.96      0.95      0.95       440
```

Support Vector Machine implementation

Dash, Ritesh, Dillip Ku Dash, and G. C. Biswal. "Classification of crop based on macronutrients and weather data using machine learning techniques." Results in Engineering 9 (2021): 100203.

```
data2 = pd.read_csv(url)
data2.head()
```

	N	P	K	temperature	humidity	ph	label
0	93	56	42	23.85754	82.25573	7.385763	Paddy
1	79	43	39	21.66628	80.70961	7.062779	Paddy
2	95	52	36	26.22917	83.83626	5.543360	Paddy
3	67	58	39	25.28272	80.54373	5.453592	Paddy
4	70	36	42	21.84107	80.72886	6.946210	Paddy

```
a = data2.drop('label', axis=1)
b = data2['label']
```

```
from sklearn.model_selection import train_test_split
a_train, a_test, b_train, b_test = train_test_split(a, b, test_size = 0.3,
                                                    shuffle = True, random_state = 0)
```

```
from sklearn import svm
model = svm.SVC()
model.fit(a_train, b_train)

b_pred=model.predict(a_test)

accuracy=accuracy_score(b_pred, b_test)
print('SVM Model accuracy score: {0:0.4f}'.format(accuracy_score(b_test, b_pred)))
```

```
SVM Model accuracy score: 0.8567
```

```
print('Training set score: {:.4f}'.format(model.score(a_train, b_train)))
print('Test set score: {:.4f}'.format(model.score(a_test, b_test)))
```

```
Training set score: 0.8895
Test set score: 0.8567
```

```
print(classification_report(b_test, b_pred))
```

```
              precision    recall  f1-score   support

      Ginger       0.61      0.93      0.74        30
       Onion       0.85      1.00      0.92        34
       Paddy       0.39      0.71      0.50        24
      Potato       1.00      0.93      0.97        30
      Pulses       0.89      0.61      0.72        28
     Pumpkin       0.78      0.76      0.77        33
         Tea       1.00      0.94      0.97        33
      Tomato       0.94      0.47      0.62        32
       Wheat       1.00      1.00      1.00        27
       apple       1.00      1.00      1.00        39
      banana       1.00      1.00      1.00        36
   blackgram       0.61      0.83      0.70        23
    chickpea       1.00      1.00      1.00        24
     coconut       0.97      1.00      0.98        30
      coffee       0.94      1.00      0.97        31
      cotton       0.94      1.00      0.97        30
      grapes       1.00      1.00      1.00        28
        jute       0.00      0.00      0.00        33
 kidneybeans       0.90      1.00      0.95        28
      lentil       0.64      0.77      0.70        30
       maize       1.00      0.93      0.96        41
       mango       0.84      1.00      0.92        38
   mothbeans       0.89      0.78      0.83        32
    mungbean       0.77      0.97      0.86        37
   muskmelon       0.89      0.86      0.87        28
      orange       0.93      0.96      0.95        28
      papaya       1.00      0.96      0.98        24
  pigeonpeas       0.75      0.52      0.61        29
 pomegranate       0.90      0.95      0.93        20
  watermelon       0.89      0.80      0.84        20

    accuracy                           0.86       900
   macro avg       0.84      0.86      0.84       900
weighted avg       0.85      0.86      0.84       900

/usr/local/lib/python3.8/dist-packages/sklearn/metrics/_classification.py:1318: UndefinedMetricWarning:

Precision and F-score are ill-defined and being set to 0.0 in labels with no predicted samples. Use `zero_division` parameter to contro

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```
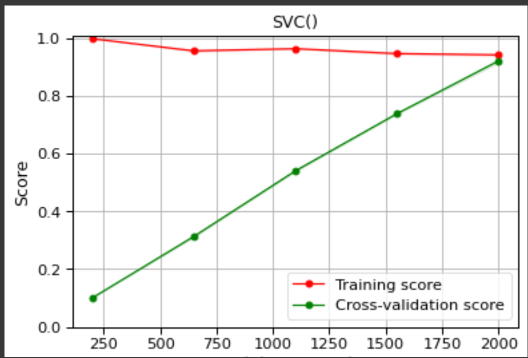
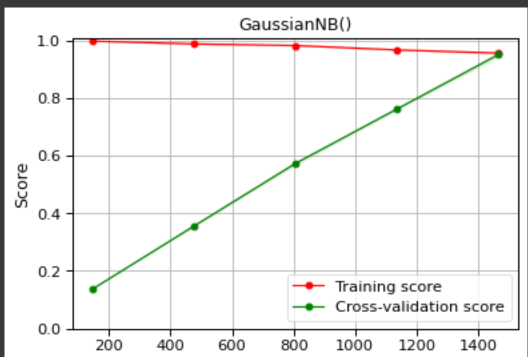

Result analysis

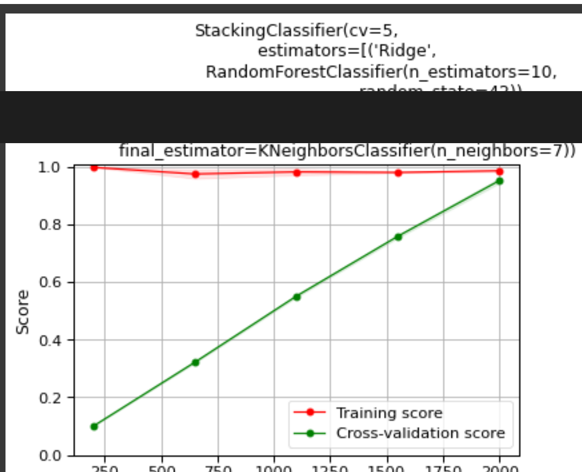
```
std = StandardScaler()
a = std.fit_transform(data2[['N','P','K','temperature','humidity','ph']])
b = data2['label']

title = model
cv = ShuffleSplit(n_splits=5, test_size=0.4, random_state=0)
plt = plot_learning_curve(model, title, a, b, cv=3, ylim=(0.0, 1.01), n_jobs=1)
plt.show()
```




```
std = StandardScaler()
a = std.fit_transform(data[['temperature','humidity','ph','rainfall']])
b = data['label']

title = model_NB1
cv = ShuffleSplit(n_splits=5, test_size=0.4, random_state=0)
plt = plot_learning_curve(model_NB1, title, a, b, cv=3, ylim=(0.0, 1.01), n_jobs=1)
plt.show()
```




```
std = StandardScaler()
a = std.fit_transform(df[['N','P','K','temperature','humidity','ph']])
b = df['label']

title = clf
cv = ShuffleSplit(n_splits=5, test_size=0.4, random_state=0)
plt3 = plot_learning_curve(clf, title, a, b, cv=3, ylim=(0.0, 1.01), n_jobs=1)
plt3.show()
```



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