Module 1: Data validation and pre-processing

In [1]:
```
import numpy as n
import pandas as p
from sklearn.preprocessing import LabelEncoder
import matplotlib.pyplot as plt
import seaborn as s
```

In [2]:
```
import warnings
warnings.filterwarnings('ignore')
```

In [3]:
```
df = p.read_csv('crop.csv') #load the dataset as dataframe
```

In [4]:
```
df.columns #Returns columns of dataframe
```

Out[4]:
```
Index(['nitrogen', 'phosphorus', 'potassium', 'temperature', 'humidity', 'ph',
       'rainfall', 'label'],
      dtype='object')
```

In [5]:
```
df.info() #Returns basic description of dataframe
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2200 entries, 0 to 2199
Data columns (total 8 columns):
 #   Column       Non-Null Count  Dtype  
---  ------       --------------  -----  
 0   nitrogen     2200 non-null   int64  
 1   phosphorus   2200 non-null   int64  
 2   potassium    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 [6]:
```
df.head(3) #Returns first 3 rows of data
```

Out[6]:

	nitrogen	phosphorus	potassium	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

In [7]:
```
df.shape #dimension of dataframe
```

Out[7]:
```
(2200, 8)
```

In [8]:
```
df.isnull() #returns True if value is NULL else returns False
```

Out[8]:

	nitrogen	phosphorus	potassium	temperature	humidity	ph	rainfall	label
0	False	False	False	False	False	False	False	False
1	False	False	False	False	False	False	False	False
2	False	False	False	False	False	False	False	False
3	False	False	False	False	False	False	False	False
4	False	False	False	False	False	False	False	False
...	...	...	...	...	...	...	...	...
2195	False	False	False	False	False	False	False	False
2196	False	False	False	False	False	False	False	False
2197	False	False	False	False	False	False	False	False
2198	False	False	False	False	False	False	False	False
2199	False	False	False	False	False	False	False	False

2200 rows × 8 columns

In [9]:
```
df.isnull().sum() #Return sum of missing values in each column
```

Out[9]:
```
nitrogen       0
phosphorus     0
potassium      0
temperature    0
humidity       0
ph             0
rainfall       0
label          0
dtype: int64
```

In [10]:
```
df.describe() #Returns numerical description
```

Out[10]:

	nitrogen	phosphorus	potassium	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 [11]:
```
sum(df.duplicated()) #Returns sum of duplicate data
```

Out[11]:
```
0
```

In [12]:
```
df.nitrogen.unique() #Returns unique values of nitrogen
```

Out[12]:
```
array([ 90,  85,  60,  74,  78,  69,  94,  89,  68,  91,  93,  77,  88,
        76,  67,  83,  98,  66,  97,  84,  73,  92,  95,  99,  63,  62,
        64,  82,  79,  65,  75,  71,  72,  70,  86,  61,  81,  80, 100,
        87,  96,  40,  23,  39,  22,  36,  32,  58,  59,  42,  28,  43,
        27,  50,  25,  31,  26,  54,  57,  49,  46,  38,  35,  52,  44,
        24,  29,  20,  56,  37,  51,  41,  34,  30,  33,  47,  53,  45,
        48,  13,   2,  17,  12,   6,  10,  19,  11,  18,  21,  16,   9,
         1,   7,   8,   0,   3,   4,   5,  14,  15,  55, 105, 108, 118,
       101, 106, 109, 117, 114, 110, 112, 111, 102, 116, 119, 107, 104,
       103, 120, 113, 115, 133, 136, 126, 121, 129, 122, 140, 131, 135,
       123, 125, 139, 132, 127, 130, 134], dtype=int64)
```

In [13]:
```
df['label'].unique() #Returns unique labels
```

Out[13]:
```
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 [14]:
```
df.potassium.sort_values().unique() #Returns unique values of potassium after sortin
```

Out[14]:
```
array([  5,   6,   7,   8,   9,  10,  11,  12,  13,  14,  15,  16,  17,
        18,  19,  20,  21,  22,  23,  24,  25,  26,  27,  28,  29,  30,
        31,  32,  33,  34,  35,  36,  37,  38,  39,  40,  41,  42,  43,
        44,  45,  46,  47,  48,  49,  50,  51,  52,  53,  54,  55,  75,
        76,  77,  78,  79,  80,  81,  82,  83,  84,  85, 195, 196, 197,
       198, 199, 200, 201, 202, 203, 204, 205], dtype=int64)
```

In [15]:
```
df['label'].value_counts() #Returns number of instances of each unique label(crop ty
```

Out[15]:
```
blackgram      100
jute           100
mungbean       100
kidneybeans    100
mango          100
lentil         100
maize          100
chickpea       100
apple          100
coconut        100
cotton         100
coffee         100
pomegranate    100
grapes         100
muskmelon      100
pigeonpeas     100
banana         100
watermelon     100
orange         100
papaya         100
mothbeans      100
rice           100
Name: label, dtype: int64
```

In [16]:
```
df.corr() #Returns pairwise correlation of the columns
```

Out[16]:

	nitrogen	phosphorus	potassium	temperature	humidity	ph	rainfall
nitrogen	1.000000	-0.231460	-0.140512	0.026504	0.190688	0.096683	0.059020

	nitrogen	phosphorus	potassium	temperature	humidity	ph	rainfall
phosphorus	-0.231460	1.000000	0.736232	-0.127541	-0.118734	-0.138019	-0.063839
potassium	-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 [17]:
```
col_to_be_encoded = ['label']
le = LabelEncoder() #method to encode and set values between 0 and k-1 for k distinc
for i in col_to_be_encoded:
    df[i] = le.fit_transform(df[i]).astype(int) #Returns encoded labels as int datat
```

In [18]:
```
df['label'].unique()
```

Out[18]:
```
array([20, 11,  3,  9, 18, 13, 14,  2, 10, 19,  1, 12,  7, 21, 15,  0, 16,
       17,  4,  6,  8,  5])
```

In [19]:
```
df.tail(3) #Returns last 3 tuples of data
```

Out[19]:

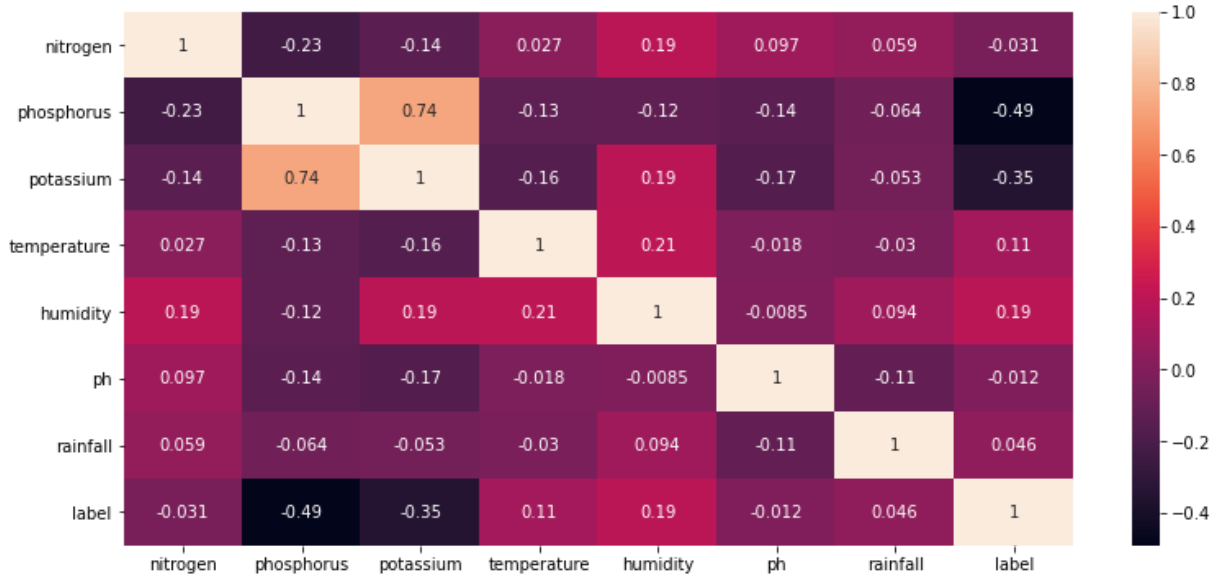
	nitrogen	phosphorus	potassium	temperature	humidity	ph	rainfall	label
2197	118	33	30	24.131797	67.225123	6.362608	173.322839	5
2198	117	32	34	26.272418	52.127394	6.758793	127.175293	5
2199	104	18	30	23.603016	60.396475	6.779833	140.937041	5

Module 2: Exploratory data analysis and data visualization

In [20]:
```
df = df.dropna() #Drop NULL values
```

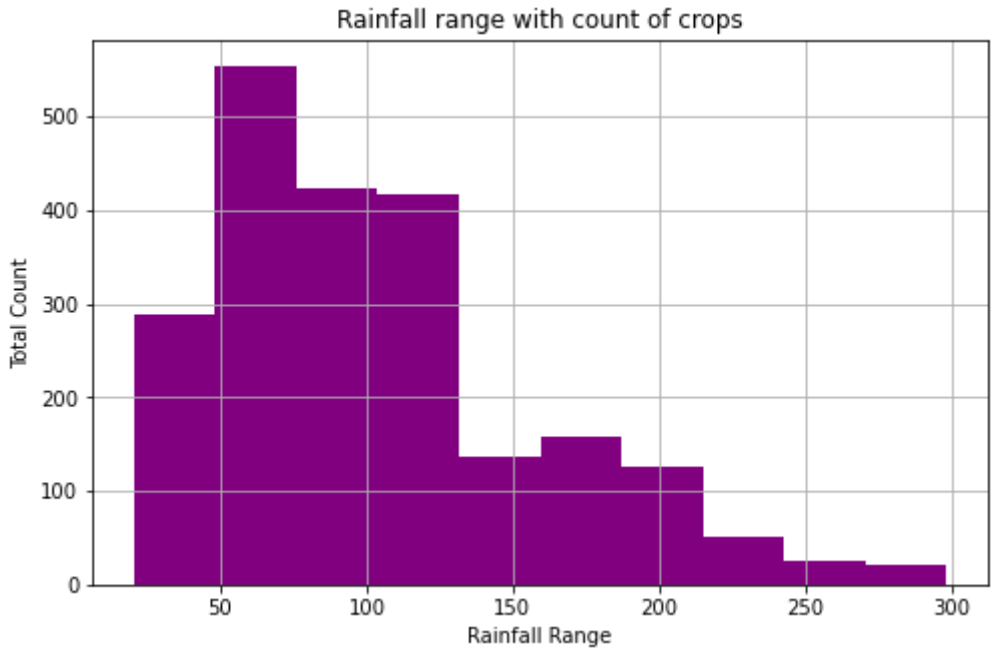
In [21]:
```
fig, ax = plt.subplots(figsize=(13,6))
s.heatmap(df.corr(), ax=ax, annot=True) #Heatmap to show correlation between feature
```

Out[21]:
```
<AxesSubplot:>
```



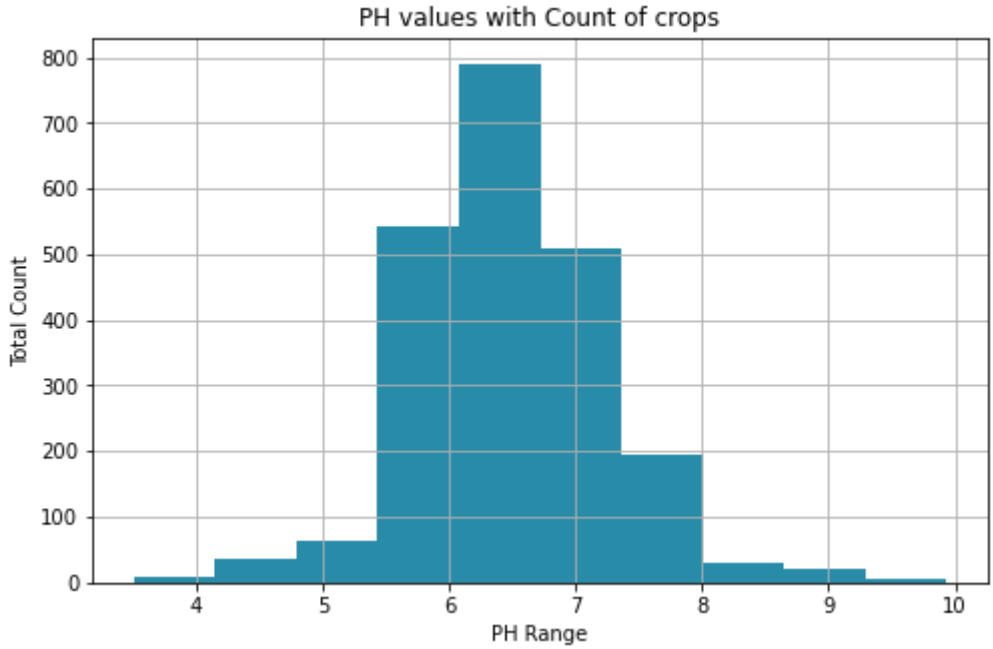
In [22]:
```
df['rainfall'].hist(figsize=(8,5), color='purple')
plt.title('Rainfall range with count of crops')
plt.xlabel('Rainfall Range')
plt.ylabel('Total Count')
```

Out[22]: Text(0, 0.5, 'Total Count')

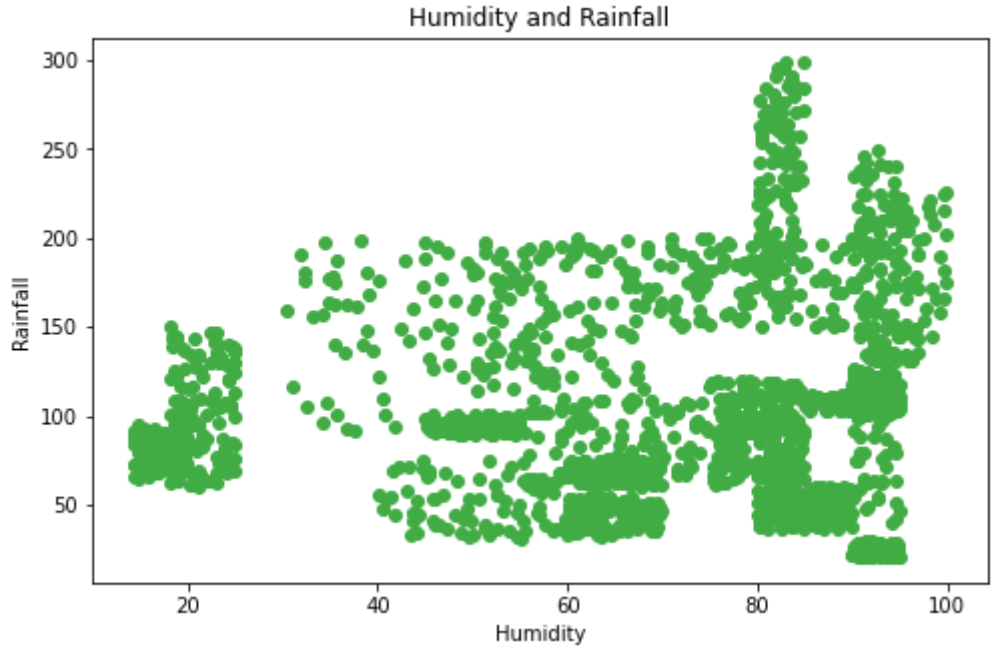


In [23]:
```
df['ph'].hist(figsize=(8,5), color='#288BA8')
plt.title('PH values with Count of crops')
plt.xlabel('PH Range')
plt.ylabel('Total Count')
```

Out[23]: Text(0, 0.5, 'Total Count')

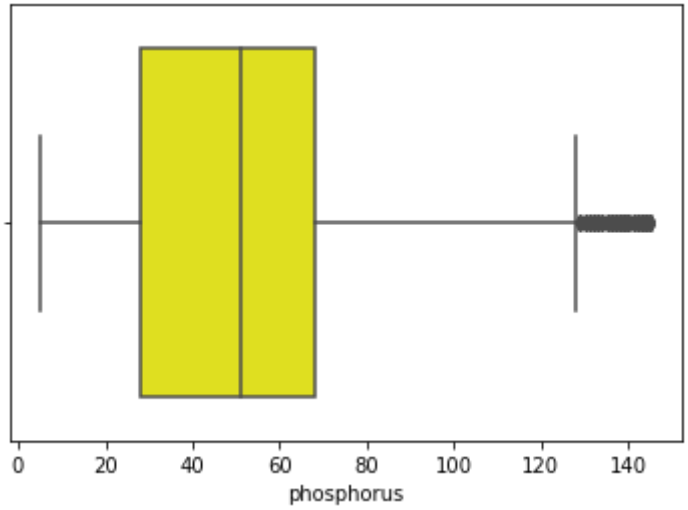


In [24]:
```
fig, ax = plt.subplots(figsize=(8,5))
ax.scatter(df['humidity'],df['rainfall'],color='#41AC44')
ax.set_title('Humidity and Rainfall')
ax.set_xlabel('Humidity')
ax.set_ylabel('Rainfall')
plt.show()
```



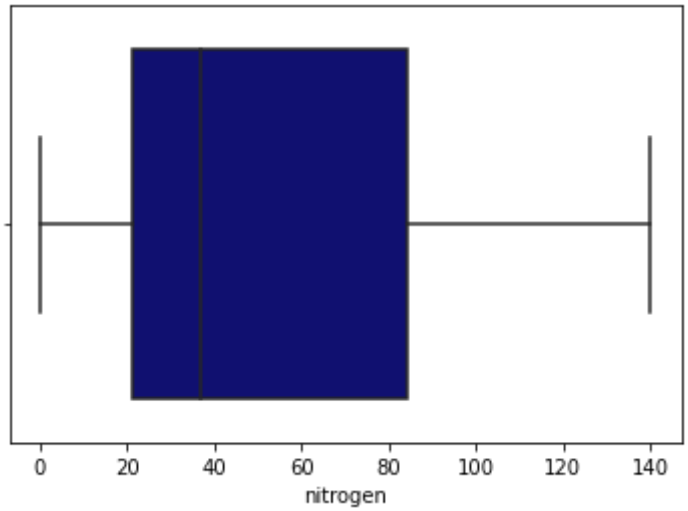
In [25]:
```
s.boxplot(df['phosphorus'], color='yellow')
```

Out[25]:
```
<AxesSubplot:xlabel='phosphorus'>
```



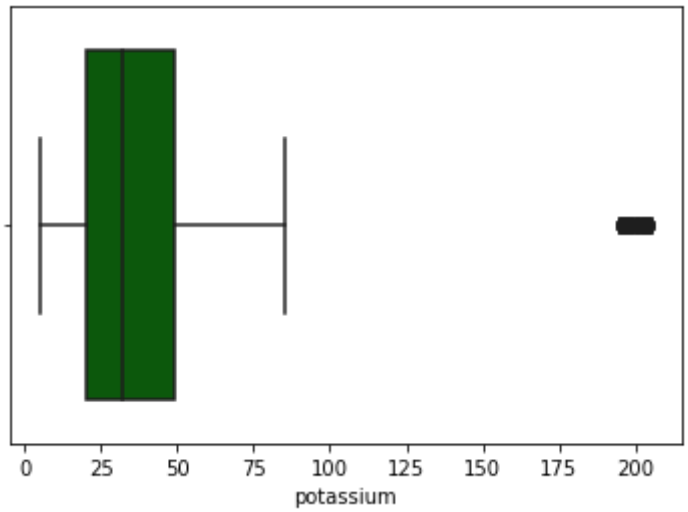
In [26]:
```
s.boxplot(df['nitrogen'], color='#000080')
```

Out[26]: <AxesSubplot:xlabel='nitrogen'>



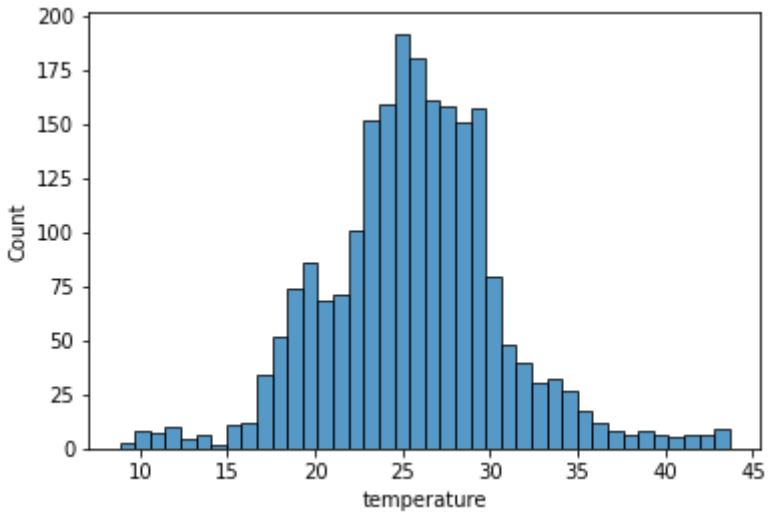
In [27]:
```
s.boxplot(df['potassium'], color='darkgreen')
```

Out[27]: <AxesSubplot:xlabel='potassium'>



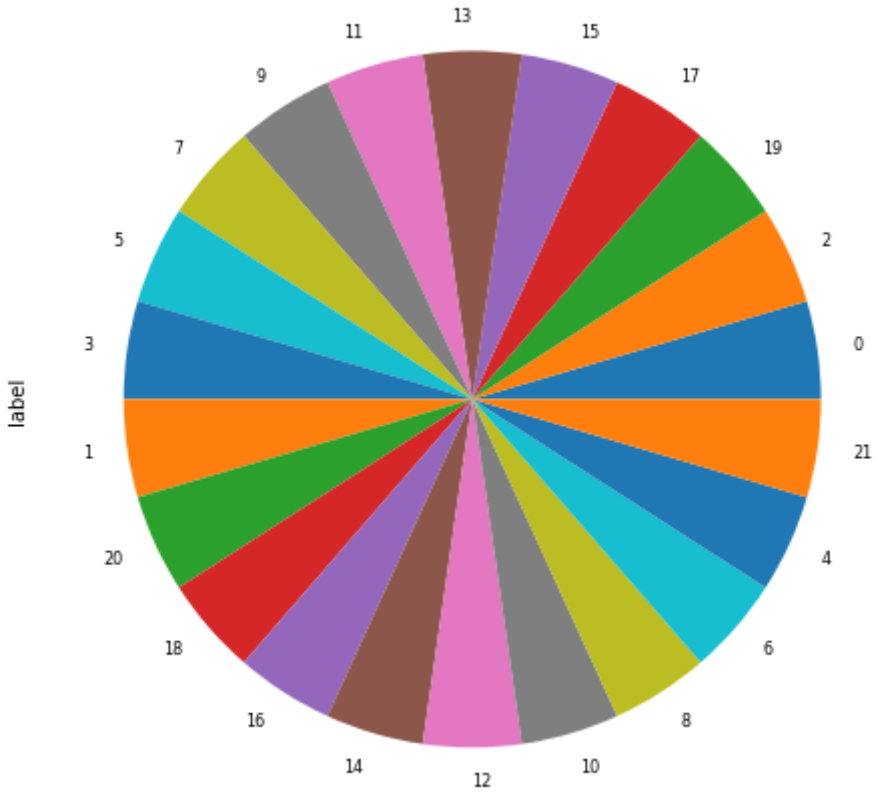
In [28]:
```
s.histplot(df['temperature'])
```

Out[28]: <AxesSubplot:xlabel='temperature', ylabel='Count'>



In [29]:
```
def PropByVar(df,variable): #Propagation by variable
    pie_var = df[variable].value_counts()
    ax = pie_var.plot.pie(figsize=(8,8), fontsize =8)
    return "Different types of crops"
PropByVar(df,'label')
```

Out[29]: 'Different types of crops'



Algorithm Implementation

In [30]:
```
from sklearn.model_selection import train_test_split
from sklearn.tree import DecisionTreeClassifier
from sklearn.naive_bayes import GaussianNB
```

```
from sklearn.ensemble import AdaBoostClassifier
from sklearn.ensemble import VotingClassifier
from sklearn.metrics import confusion_matrix, classification_report, accuracy_score,
import joblib
from sklearn.model_selection import cross_val_score
```

In [31]:
```
inputs = df.drop(labels='label', axis=1) #takes all features except label as input
output = df.loc[:,'label'] #Returns label(crop type) as output
```

In [32]:
```
X_train, X_test, y_train, y_test = train_test_split(inputs, output, test_size=0.3, r
print("Number of Training Datasets: ", len(X_train))
print("Number of Testing Dataset: ", len(X_test))
print("Total Number of Datasets: ", len(X_train)+len(X_test))
```

```
Number of Training Datasets:  1540
Number of Testing Dataset:  660
Total Number of Datasets:  2200
```

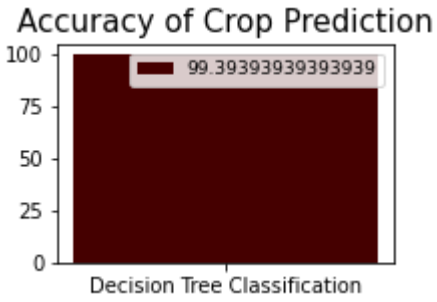
Module 3 Decision Tree Classifier

In [33]:
```
#Model Training
dt = DecisionTreeClassifier()
dt.fit(X_train,y_train)
predicted_dt = dt.predict(X_test)
```

In [34]:
```
#Getting Accuracy
accuracy = accuracy_score(y_test,predicted_dt) # accuracy: (tp + tn) / (p + n)
print('Accuracy of Decision Tree Classifier is: ',accuracy*100)
```

```
Accuracy of Decision Tree Classifier is:  99.39393939393939
```

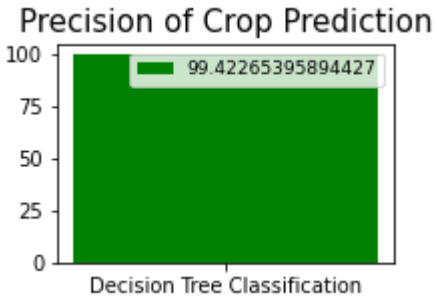
In [35]:
```
DT1=accuracy.mean() *100
def graph():
    data=[DT1]
    alg="Decision Tree Classification"
    plt.figure(figsize=(3,2))
    b=plt.bar(alg,data,color=("#450000"))
    plt.title("Accuracy of Crop Prediction",fontsize=15)
    plt.legend(b,data,fontsize=9)
graph()
```



In [36]:
```
#Getting Precision
precision = precision_score(y_test,predicted_dt,average='weighted') # precision tp /
#weighted average takes mean of all classes' scores
print('Precision of Decision Tree Classifier is: ',precision*100)
```

```
Precision of Decision Tree Classifier is:  99.42265395894427
```

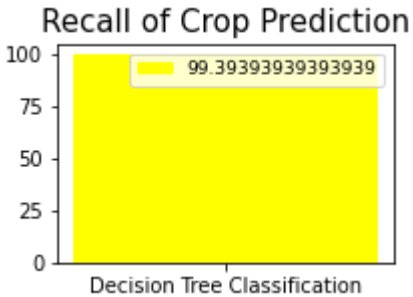
In [37]:
```
DT2=precision.mean() *100
def graph():
    data=[DT2]
    alg="Decision Tree Classification"
    plt.figure(figsize=(3,2))
    b=plt.bar(alg,data,color=("green"))
    plt.title("Precision of Crop Prediction",fontsize=15)
    plt.legend(b,data,fontsize=9)
graph()
```



In [38]:
```
#Getting Recall
recall = recall_score(y_test,predicted_dt,average='weighted') # recall: tp / (tp + f
print('Recall of Decision Tree Classifier is: ',recall*100)
```

```
Recall of Decision Tree Classifier is:  99.39393939393939
```

In [39]:
```
DT3=recall.mean() *100
def graph():
    data=[DT3]
    alg="Decision Tree Classification"
    plt.figure(figsize=(3,2))
    b=plt.bar(alg,data,color=("yellow"))
    plt.title("Recall of Crop Prediction",fontsize=15)
    plt.legend(b,data,fontsize=9)
graph()
```

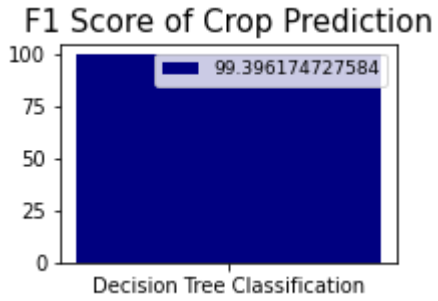


In [40]:
```
#Getting F1 Score
f1 = f1_score(y_test,predicted_dt,average='weighted') # f1: 2 tp / (2 tp + fp + fn)
print('F1 Score of Decision Tree Classifier is: ',f1*100)
```

```
F1 Score of Decision Tree Classifier is:  99.396174727584
```

In [41]:
```
DT4=f1.mean() *100
def graph():
    data=[DT4]
    alg="Decision Tree Classification"
    plt.figure(figsize=(3,2))
```

```
    b=plt.bar(alg,data,color=("#000080"))
    plt.title("F1 Score of Crop Prediction",fontsize=15)
    plt.legend(b,data,fontsize=9)
graph()
```



In [42]:

```
#Classification Report
cr = classification_report(y_test,predicted_dt)
print('Classification report\n',cr)
```

```
Classification report
              precision    recall  f1-score   support

           0       1.00      1.00      1.00        30
           1       1.00      1.00      1.00        30
           2       0.94      1.00      0.97        30
           3       1.00      1.00      1.00        30
           4       1.00      0.97      0.98        30
           5       1.00      0.97      0.98        30
           6       0.97      1.00      0.98        30
           7       1.00      1.00      1.00        30
           8       1.00      1.00      1.00        30
           9       1.00      1.00      1.00        30
          10       1.00      1.00      1.00        30
          11       1.00      0.97      0.98        30
          12       1.00      1.00      1.00        30
          13       1.00      0.97      0.98        30
          14       1.00      1.00      1.00        30
          15       1.00      1.00      1.00        30
          16       0.97      1.00      0.98        30
          17       1.00      1.00      1.00        30
          18       1.00      1.00      1.00        30
          19       1.00      1.00      1.00        30
          20       1.00      1.00      1.00        30
          21       1.00      1.00      1.00        30

    accuracy                           0.99       660
   macro avg       0.99      0.99      0.99       660
weighted avg       0.99      0.99      0.99       660
```

In [43]:

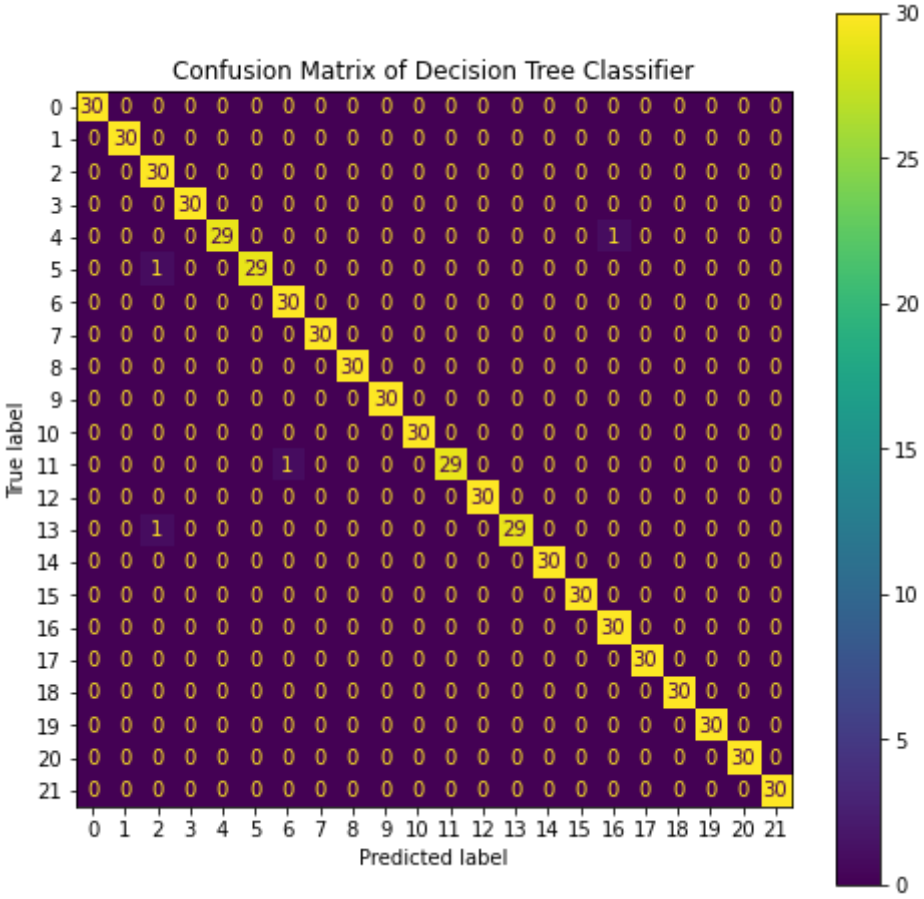
```
#Confusion Matrix
cm = confusion_matrix(y_test,predicted_dt)
print('Confusion matrix\n',cm)
```

```
Confusion matrix
 [[30  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0]
 [ 0 30  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0]
 [ 0  0 30  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0]
 [ 0  0  0 30  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0]
 [ 0  0  0  0 29  0  0  0  0  0  0  0  0  0  0  0  1  0  0  0  0  0]
 [ 0  0  1  0  0 29  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0]
 [ 0  0  0  0  0  0 30  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0]
 [ 0  0  0  0  0  0  0 30  0  0  0  0  0  0  0  0  0  0  0  0  0  0]
 [ 0  0  0  0  0  0  0  0 30  0  0  0  0  0  0  0  0  0  0  0  0  0]
 [ 0  0  0  0  0  0  0  0  0 30  0  0  0  0  0  0  0  0  0  0  0  0]
```

```
[ 0  0  0  0  0  0  0  0  0  0 30  0  0  0  0  0  0  0  0  0  0]
[ 0  0  0  0  0  0  1  0  0  0  0 29  0  0  0  0  0  0  0  0  0]
[ 0  0  0  0  0  0  0  0  0  0  0  0 30  0  0  0  0  0  0  0  0]
[ 0  0  1  0  0  0  0  0  0  0  0  0  0 29  0  0  0  0  0  0  0]
[ 0  0  0  0  0  0  0  0  0  0  0  0  0  0 30  0  0  0  0  0  0]
[ 0  0  0  0  0  0  0  0  0  0  0  0  0  0  0 30  0  0  0  0  0]
[ 0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0 30  0  0  0  0]
[ 0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0 30  0  0  0]
[ 0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0 30  0  0]
[ 0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0 30  0]
[ 0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0 30]]
```

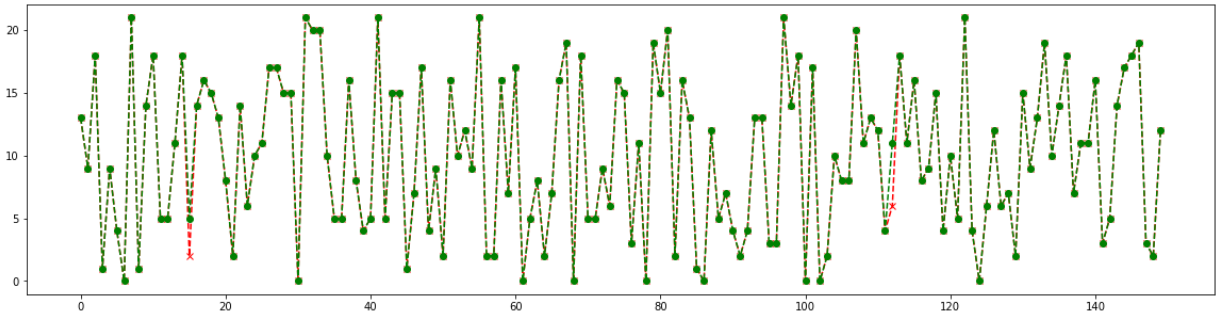
In [44]:

```
fig, ax = plt.subplots(figsize=(8,8))
plot_confusion_matrix(dt, X_test, y_test, ax=ax)
plt.title('Confusion Matrix of Decision Tree Classifier')
plt.show()
```



In [45]:

```
DF1 = p.DataFrame()
DF1["y_test"] = y_test
DF1["predicted"] = predicted_dt
DF1.reset_index(inplace=True)
plt.figure(figsize=(20, 5))
plt.plot(DF1["predicted"][:150], marker='x', linestyle='dashed', color='red')
plt.plot(DF1["y_test"][:150],  marker='o', linestyle='dashed', color='green')
plt.show()
```



In [46]:
```
#Saving Model
joblib.dump(dt,'dt.pkl')
```

Out[46]:
```
['dt.pkl']
```

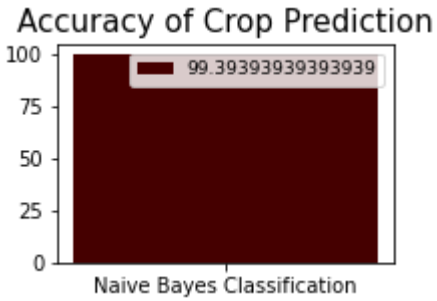
Module 4 Gaussian Naive Bayes

In [47]:
```
#Model Training
nb = GaussianNB()
nb.fit(X_train,y_train)
predicted_nb = nb.predict(X_test)
```

In [48]:
```
#Getting Accuracy
accuracy = accuracy_score(y_test,predicted_nb) # accuracy: (tp + tn) / (p + n)
print('Accuracy of Naive Bayes is: ',accuracy*100)
```

```
Accuracy of Naive Bayes is:  99.39393939393939
```

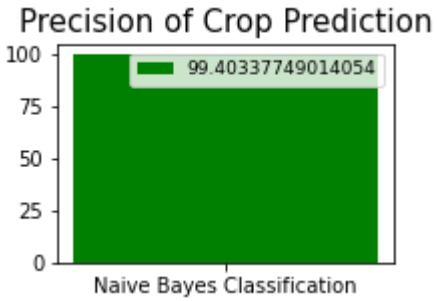
In [49]:
```
NB1=accuracy.mean() *100
def graph():
    data=[NB1]
    alg="Naive Bayes Classification"
    plt.figure(figsize=(3,2))
    b=plt.bar(alg,data,color=("#450000"))
    plt.title("Accuracy of Crop Prediction",fontsize=15)
    plt.legend(b,data,fontsize=9)
graph()
```



In [50]:
```
#Getting Precision
precision = precision_score(y_test,predicted_nb,average='weighted') # precision tp /
print('Precision of Naive Bayes is: ',precision*100)
```

```
Precision of Naive Bayes is:  99.40337749014054
```

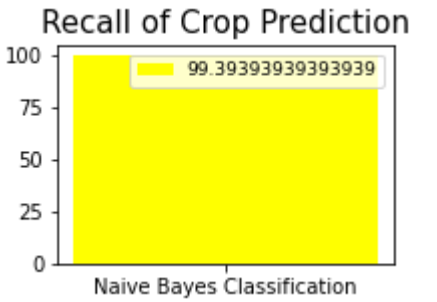
In [51]:
```
NB2=precision.mean() *100
def graph():
    data=[NB2]
    alg="Naive Bayes Classification"
    plt.figure(figsize=(3,2))
    b=plt.bar(alg,data,color=("green"))
    plt.title("Precision of Crop Prediction",fontsize=15)
    plt.legend(b,data,fontsize=9)
graph()
```



In [52]:
```
#Getting Recall
recall = recall_score(y_test,predicted_nb,average='weighted') # recall: tp / (tp + f
print('Recall of Naive Bayes is: ',recall*100)
```

```
Recall of Naive Bayes is:  99.39393939393939
```

In [53]:
```
NB3=recall.mean() *100
def graph():
    data=[NB3]
    alg="Naive Bayes Classification"
    plt.figure(figsize=(3,2))
    b=plt.bar(alg,data,color=("yellow"))
    plt.title("Recall of Crop Prediction",fontsize=15)
    plt.legend(b,data,fontsize=9)
graph()
```

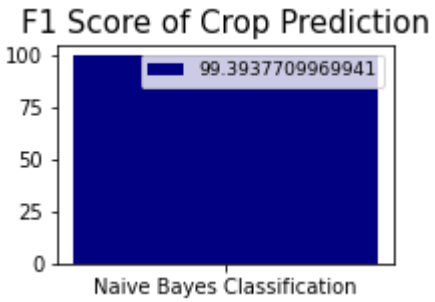


In [54]:
```
#Getting F1 Score
f1 = f1_score(y_test,predicted_nb,average='weighted') # f1: 2 tp / (2 tp + fp + fn)
print('F1 Score of Naive Bayes is: ',f1*100)
```

```
F1 Score of Naive Bayes is:  99.3937709969941
```

In [55]:
```
NB4=f1.mean() *100
def graph():
    data=[NB4]
    alg="Naive Bayes Classification"
    plt.figure(figsize=(3,2))
    b=plt.bar(alg,data,color=("#000080"))
```

```
    plt.title("F1 Score of Crop Prediction",fontsize=15)
    plt.legend(b,data,fontsize=9)
graph()
```



In [56]:

```
#Classification Report
cr = classification_report(y_test,predicted_nb)
print('Classification report\n',cr)
```

```
Classification report
              precision    recall  f1-score   support

           0       1.00      1.00      1.00        30
           1       1.00      1.00      1.00        30
           2       1.00      1.00      1.00        30
           3       1.00      1.00      1.00        30
           4       1.00      1.00      1.00        30
           5       1.00      1.00      1.00        30
           6       0.97      1.00      0.98        30
           7       1.00      1.00      1.00        30
           8       0.97      0.93      0.95        30
           9       1.00      1.00      1.00        30
          10       1.00      1.00      1.00        30
          11       1.00      0.97      0.98        30
          12       1.00      1.00      1.00        30
          13       1.00      1.00      1.00        30
          14       1.00      1.00      1.00        30
          15       1.00      1.00      1.00        30
          16       1.00      1.00      1.00        30
          17       1.00      1.00      1.00        30
          18       1.00      1.00      1.00        30
          19       1.00      1.00      1.00        30
          20       0.94      0.97      0.95        30
          21       1.00      1.00      1.00        30

    accuracy                           0.99       660
   macro avg       0.99      0.99      0.99       660
weighted avg       0.99      0.99      0.99       660
```

In [57]:

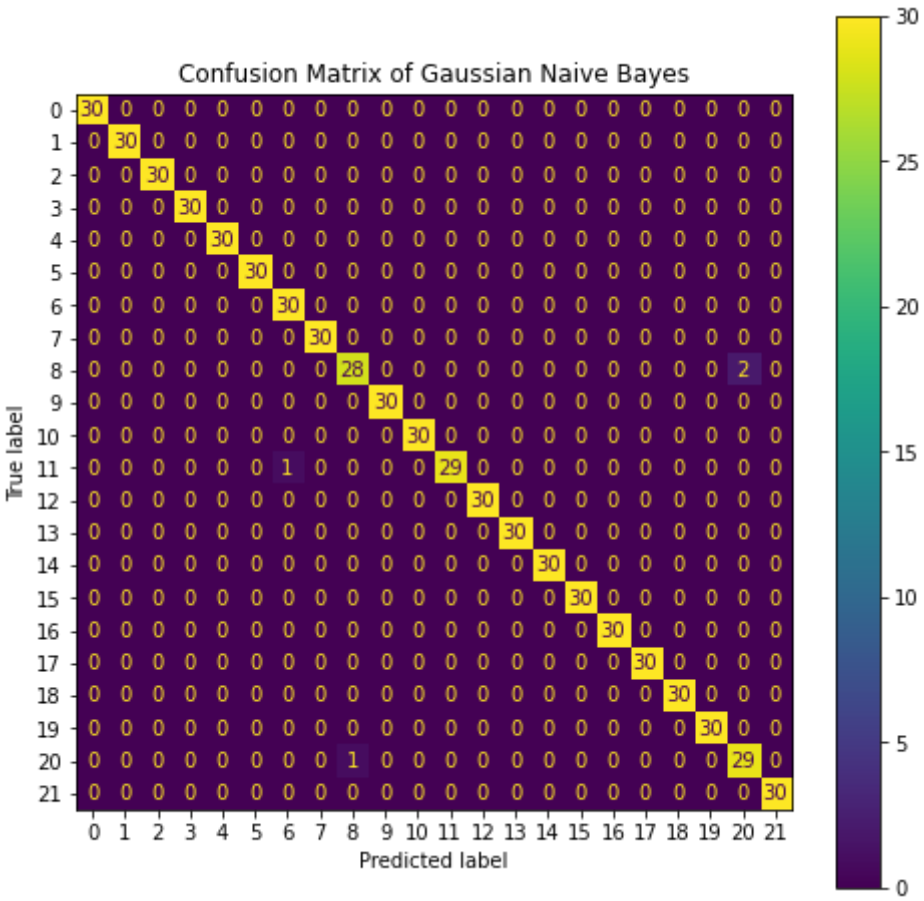
```
#Confusion Matrix
cm = confusion_matrix(y_test,predicted_nb)
print('Confusion matrix\n',cm)
```

```
Confusion matrix
 [[30  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0]
 [ 0 30  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0]
 [ 0  0 30  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0]
 [ 0  0  0 30  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0]
 [ 0  0  0  0 30  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0]
 [ 0  0  0  0  0 30  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0]
 [ 0  0  0  0  0  0 30  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0]
 [ 0  0  0  0  0  0  0 30  0  0  0  0  0  0  0  0  0  0  0  0  0  0]
 [ 0  0  0  0  0  0  0  0 28  0  0  0  0  0  0  0  0  0  0  0  2  0]
 [ 0  0  0  0  0  0  0  0  0 30  0  0  0  0  0  0  0  0  0  0  0  0]
 [ 0  0  0  0  0  0  0  0  0  0 30  0  0  0  0  0  0  0  0  0  0  0]
 [ 0  0  0  0  0  0  1  0  0  0  0 29  0  0  0  0  0  0  0  0  0  0]
```

```
[ 0  0  0  0  0  0  0  0  0  0  0  0 30  0  0  0  0  0  0  0  0  0]
[ 0  0  0  0  0  0  0  0  0  0  0  0  0 30  0  0  0  0  0  0  0  0]
[ 0  0  0  0  0  0  0  0  0  0  0  0  0  0 30  0  0  0  0  0  0  0]
[ 0  0  0  0  0  0  0  0  0  0  0  0  0  0  0 30  0  0  0  0  0  0]
[ 0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0 30  0  0  0  0  0]
[ 0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0 30  0  0  0  0]
[ 0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0 30  0  0  0]
[ 0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0 30  0  0]
[ 0  0  0  0  0  0  0  0  1  0  0  0  0  0  0  0  0  0  0  0 29  0]
[ 0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0 30]]
```

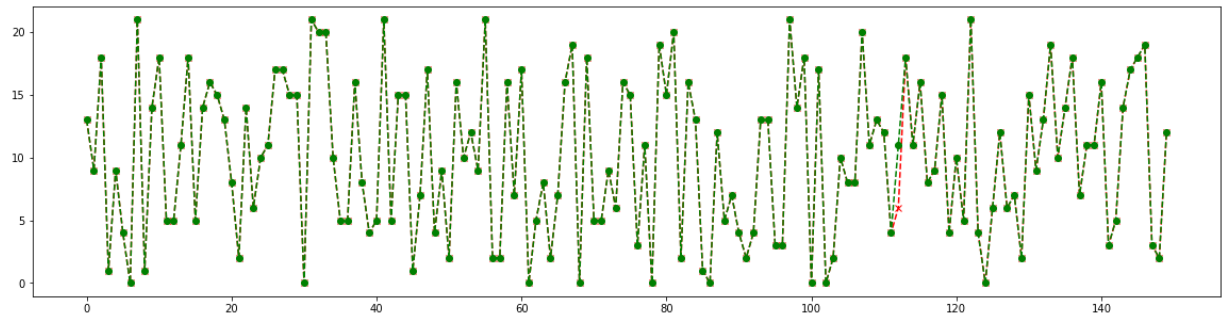
In [58]:

```
fig, ax = plt.subplots(figsize=(8,8))
plot_confusion_matrix(nb, X_test, y_test, ax=ax)
plt.title('Confusion Matrix of Gaussian Naive Bayes')
plt.show()
```



In [59]:

```
DF2 = p.DataFrame()
DF2["y_test"] = y_test
DF2["predicted"] = predicted_nb
DF2.reset_index(inplace=True)
plt.figure(figsize=(20, 5))
plt.plot(DF2["predicted"][:150], marker='x', linestyle='dashed', color='red')
plt.plot(DF2["y_test"][:150],  marker='o', linestyle='dashed', color='green')
plt.show()
```



In [60]:
```
#Saving Model
joblib.dump(nb,'nb.pkl')
```

Out[60]: ['nb.pkl']

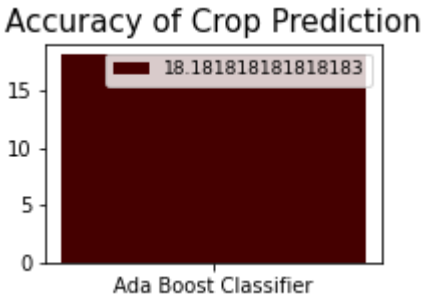
Module 5 AdaBoost classifier

In [61]:
```
#Model Training
ab = AdaBoostClassifier()
ab.fit(X_train,y_train)
predicted_ab = ab.predict(X_test)
```

In [62]:
```
#Getting Accuracy
accuracy = accuracy_score(y_test,predicted_ab) # accuracy: (tp + tn) / (p + n)
print('Accuracy of Ada Boost Classifier is: ',accuracy*100)
```

```
Accuracy of Ada Boost Classifier is:  18.181818181818183
```

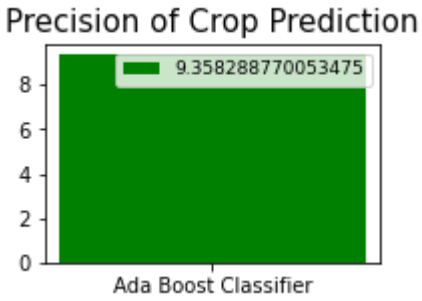
In [63]:
```
AB1=accuracy.mean() *100
def graph():
    data=[AB1]
    alg="Ada Boost Classifier"
    plt.figure(figsize=(3,2))
    b=plt.bar(alg,data,color=("#450000"))
    plt.title("Accuracy of Crop Prediction",fontsize=15)
    plt.legend(b,data,fontsize=9)
graph()
```



In [64]:
```
#Getting Precision
precision = precision_score(y_test,predicted_ab,average='weighted') # precision tp /
print('Precision of Ada Boost Classifier is: ',precision*100)
```

```
Precision of Ada Boost Classifier is:  9.358288770053475
```

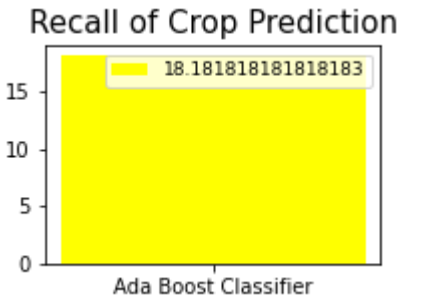
In [65]:
```
AB2=precision.mean() *100
def graph():
    data=[AB2]
    alg="Ada Boost Classifier"
    plt.figure(figsize=(3,2))
    b=plt.bar(alg,data,color=("green"))
    plt.title("Precision of Crop Prediction",fontsize=15)
    plt.legend(b,data,fontsize=9)
graph()
```



In [66]:
```
#Getting Recall
recall = recall_score(y_test,predicted_ab,average='weighted') # recall: tp / (tp + f
print('Recall of Ada Boost Classifier is: ',recall*100)
```

```
Recall of Ada Boost Classifier is:  18.181818181818183
```

In [67]:
```
AB3=recall.mean() *100
def graph():
    data=[AB3]
    alg="Ada Boost Classifier"
    plt.figure(figsize=(3,2))
    b=plt.bar(alg,data,color=("yellow"))
    plt.title("Recall of Crop Prediction",fontsize=15)
    plt.legend(b,data,fontsize=9)
graph()
```

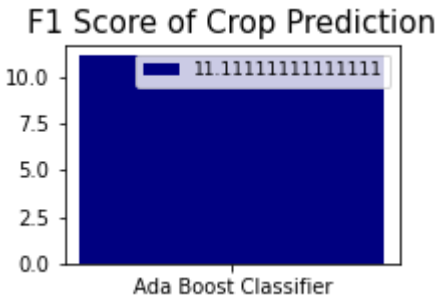


In [68]:
```
#Getting F1 Score
f1 = f1_score(y_test,predicted_ab,average='weighted') # f1: 2 tp / (2 tp + fp + fn)
print('F1 Score of Ada Boost Classifier is: ',f1*100)
```

```
F1 Score of Ada Boost Classifier is:  11.11111111111111
```

In [69]:
```
AB4=f1.mean() *100
def graph():
    data=[AB4]
    alg="Ada Boost Classifier"
    plt.figure(figsize=(3,2))
    b=plt.bar(alg,data,color=("#000080"))
```

```
    plt.title("F1 Score of Crop Prediction",fontsize=15)
    plt.legend(b,data,fontsize=9)
graph()
```



In [70]:

```
#Classification Report
cr = classification_report(y_test,predicted_ab)
print('Classification report\n',cr)
```

```
Classification report
               precision    recall  f1-score   support

           0       0.50      1.00      0.67        30
           1       0.06      1.00      0.11        30
           2       0.00      0.00      0.00        30
           3       0.50      1.00      0.67        30
           4       0.00      0.00      0.00        30
           5       0.00      0.00      0.00        30
           6       0.00      0.00      0.00        30
           7       0.00      0.00      0.00        30
           8       0.00      0.00      0.00        30
           9       0.00      0.00      0.00        30
          10       0.00      0.00      0.00        30
          11       0.00      0.00      0.00        30
          12       0.00      0.00      0.00        30
          13       0.00      0.00      0.00        30
          14       0.00      0.00      0.00        30
          15       1.00      1.00      1.00        30
          16       0.00      0.00      0.00        30
          17       0.00      0.00      0.00        30
          18       0.00      0.00      0.00        30
          19       0.00      0.00      0.00        30
          20       0.00      0.00      0.00        30
          21       0.00      0.00      0.00        30

    accuracy                           0.18       660
   macro avg       0.09      0.18      0.11       660
weighted avg       0.09      0.18      0.11       660
```

In [71]:

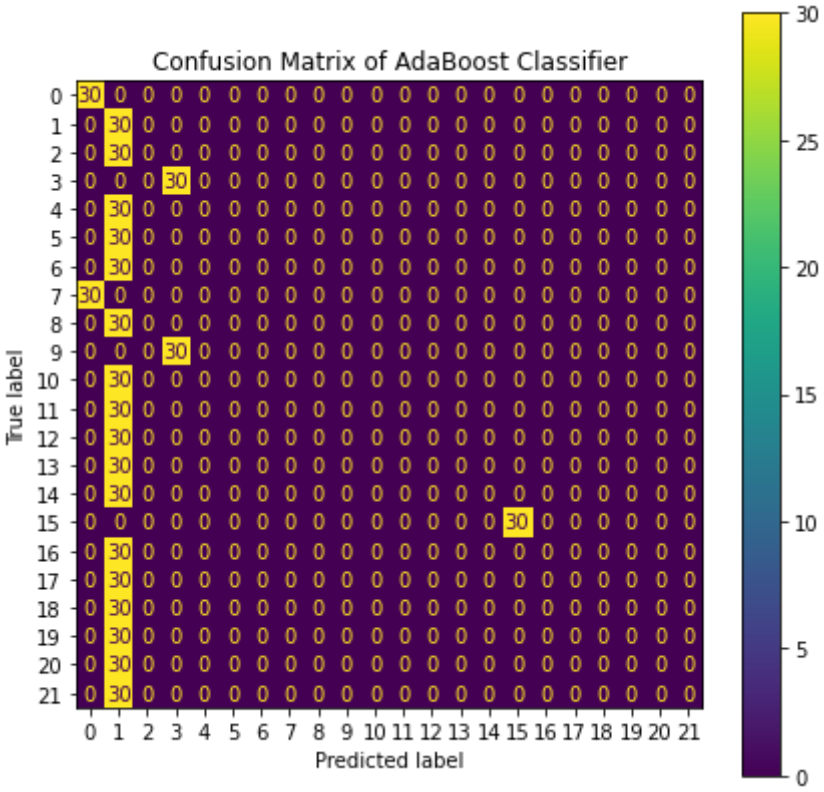
```
#Confusion Matrix
cm = confusion_matrix(y_test,predicted_ab)
print('Confusion matrix\n',cm)
```

```
Confusion matrix
 [[30  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0]
 [ 0 30  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0]
 [ 0 30  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0]
 [ 0  0  0 30  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0]
 [ 0 30  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0]
 [ 0 30  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0]
 [ 0 30  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0]
 [30  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0]
 [ 0 30  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0]
 [ 0  0  0 30  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0]
 [ 0 30  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0]
 [ 0 30  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0]
```

```
[ 0 30  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0]
[ 0 30  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0]
[ 0 30  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0]
[ 0  0  0  0  0  0  0  0  0  0  0  0  0  0  0 30  0  0  0  0  0  0]
[ 0 30  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0]
[ 0 30  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0]
[ 0 30  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0]
[ 0 30  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0]
[ 0 30  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0]
[ 0 30  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0]]
```

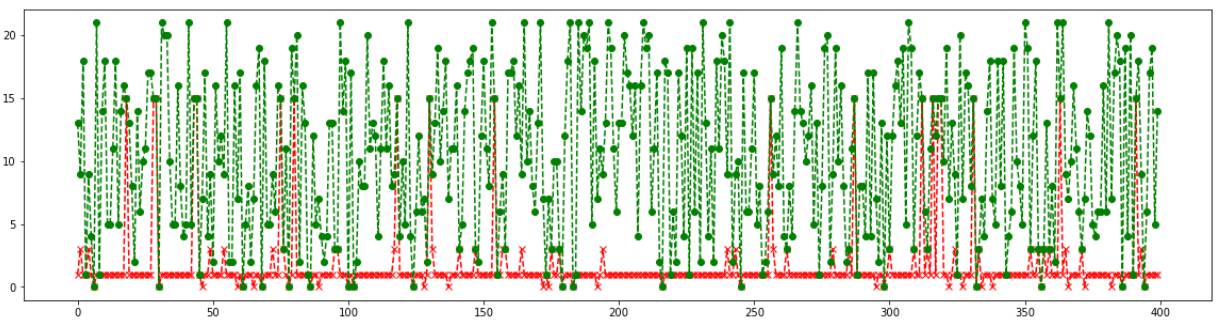
In [72]:

```
fig, ax = plt.subplots(figsize=(7,7))
plot_confusion_matrix(ab, X_test, y_test, ax=ax)
plt.title('Confusion Matrix of AdaBoost Classifier')
plt.show()
```



In [73]:

```
DF3= p.DataFrame()
DF3["y_test"] = y_test
DF3["predicted"] = predicted_ab
DF3.reset_index(inplace=True)
plt.figure(figsize=(20, 5))
plt.plot(DF3["predicted"][:400], marker='x', linestyle='dashed', color='red')
plt.plot(DF3["y_test"][:400],  marker='o', linestyle='dashed', color='green')
plt.show()
```



In [74]:
```
#Saving Model\
joblib.dump(ab,'ab.pkl')
```

Out[74]: ['ab.pkl']

Module 6 Voting Classifier

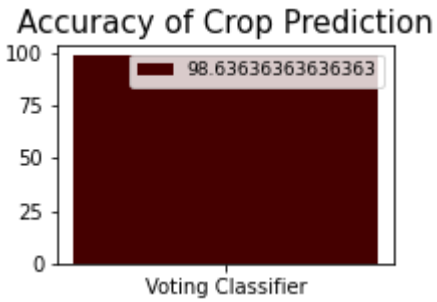
In [75]:
```
vot_clf = VotingClassifier(estimators=[('DecisionTree', dt), ('NaiveBayes', nb), ('A
```

In [76]:
```
vot_clf.fit(X_train, y_train)
pred_vtng = vot_clf.predict(X_test)
```

In [77]:
```
#Getting Accuracy
accuracy = accuracy_score(y_test,pred_vtng) # accuracy: (tp + tn) / (p + n)
print('Accuracy of Voting Classifier is: ',accuracy*100)
```

```
Accuracy of Voting Classifier is:  98.63636363636363
```

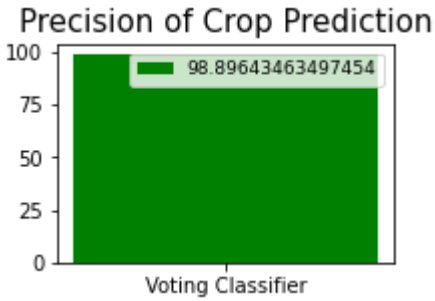
In [78]:
```
VC1=accuracy.mean() *100
def graph():
    data=[VC1]
    alg="Voting Classifier"
    plt.figure(figsize=(3,2))
    b=plt.bar(alg,data,color=("#450000"))
    plt.title("Accuracy of Crop Prediction",fontsize=15)
    plt.legend(b,data,fontsize=9)
graph()
```



In [79]:
```
#Getting Precision
precision = precision_score(y_test,pred_vtng,average='weighted') # precision tp / (t
print('Precision of Voting Classifier is: ',precision*100)
```

```
Precision of Voting Classifier is:  98.89643463497454
```

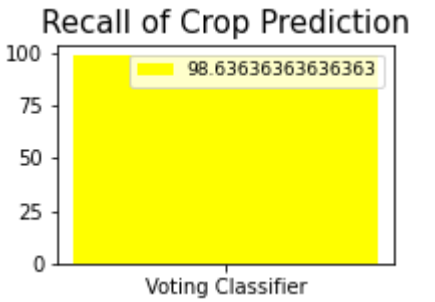
In [80]:
```
VC2=precision.mean() *100
def graph():
    data=[VC2]
    alg="Voting Classifier"
    plt.figure(figsize=(3,2))
    b=plt.bar(alg,data,color=("green"))
    plt.title("Precision of Crop Prediction",fontsize=15)
    plt.legend(b,data,fontsize=9)
graph()
```



In [81]:
```
#Getting Recall
recall = recall_score(y_test,pred_vtng,average='weighted') # recall: tp / (tp + fn)
print('Recall of Voting Classifier is: ',recall*100)
```

```
Recall of Voting Classifier is:  98.63636363636363
```

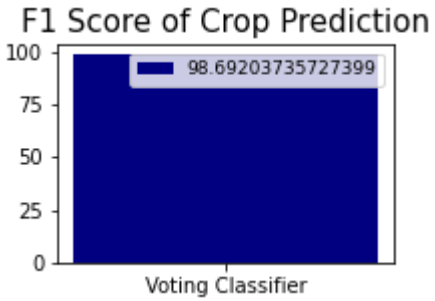
In [82]:
```
VC3=recall.mean() *100
def graph():
    data=[VC3]
    alg="Voting Classifier"
    plt.figure(figsize=(3,2))
    b=plt.bar(alg,data,color=("yellow"))
    plt.title("Recall of Crop Prediction",fontsize=15)
    plt.legend(b,data,fontsize=9)
graph()
```



In [83]:
```
#Getting F1 Score
f1 = f1_score(y_test,pred_vtng,average='weighted') # f1: 2 tp / (2 tp + fp + fn)
print('F1 Score of Voting Classifier is: ',f1*100)
```

```
F1 Score of Voting Classifier is:  98.69203735727399
```

In [84]:
```
VC4=f1.mean() *100
def graph():
    data=[VC4]
    alg="Voting Classifier"
    plt.figure(figsize=(3,2))
    b=plt.bar(alg,data,color=("#000080"))
    plt.title("F1 Score of Crop Prediction",fontsize=15)
    plt.legend(b,data,fontsize=9)
graph()
```



In [85]:

```
#Classification Report
cr = classification_report(y_test,pred_vtng)
print('Classification report\n',cr)
```

```
Classification report
              precision    recall  f1-score   support

           0       1.00      1.00      1.00        30
           1       0.79      1.00      0.88        30
           2       1.00      1.00      1.00        30
           3       1.00      1.00      1.00        30
           4       1.00      0.97      0.98        30
           5       1.00      0.97      0.98        30
           6       0.97      1.00      0.98        30
           7       1.00      1.00      1.00        30
           8       1.00      0.93      0.97        30
           9       1.00      1.00      1.00        30
          10       1.00      1.00      1.00        30
          11       1.00      0.97      0.98        30
          12       1.00      1.00      1.00        30
          13       1.00      0.97      0.98        30
          14       1.00      1.00      1.00        30
          15       1.00      1.00      1.00        30
          16       1.00      1.00      1.00        30
          17       1.00      0.93      0.97        30
          18       1.00      1.00      1.00        30
          19       1.00      1.00      1.00        30
          20       1.00      0.97      0.98        30
          21       1.00      1.00      1.00        30

    accuracy                           0.99       660
   macro avg       0.99      0.99      0.99       660
weighted avg       0.99      0.99      0.99       660
```

In [86]:

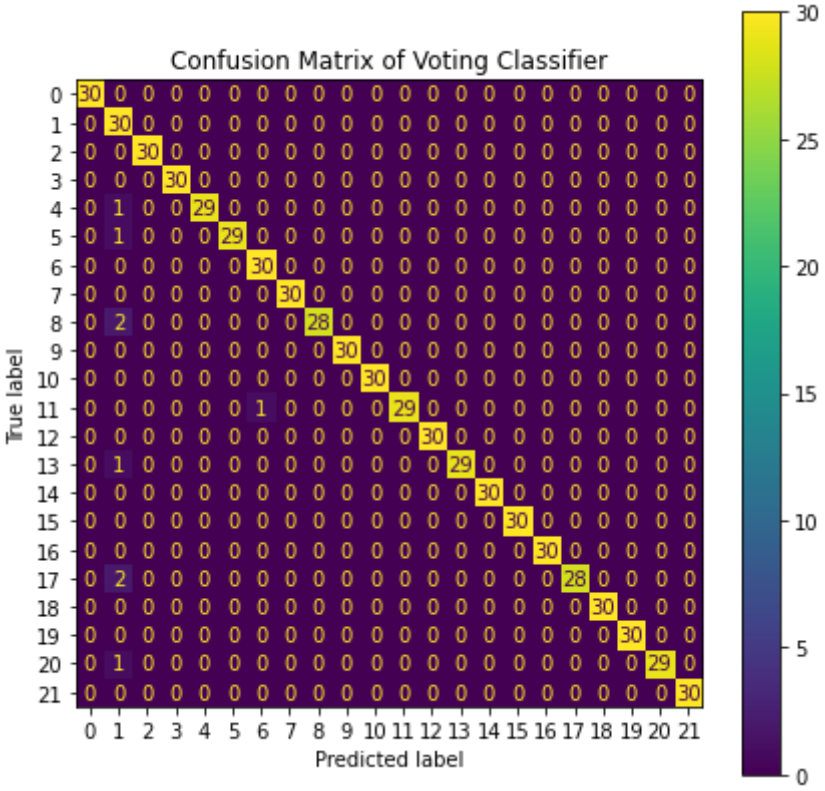
```
#Confusion Matrix
cm = confusion_matrix(y_test,pred_vtng)
print('Confusion matrix\n',cm)
```

```
Confusion matrix
 [[30  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0]
 [ 0 30  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0]
 [ 0  0 30  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0]
 [ 0  0  0 30  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0]
 [ 0  1  0  0 29  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0]
 [ 0  1  0  0  0 29  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0]
 [ 0  0  0  0  0  0 30  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0]
 [ 0  0  0  0  0  0  0 30  0  0  0  0  0  0  0  0  0  0  0  0  0  0]
 [ 0  2  0  0  0  0  0  0 28  0  0  0  0  0  0  0  0  0  0  0  0  0]
 [ 0  0  0  0  0  0  0  0  0 30  0  0  0  0  0  0  0  0  0  0  0  0]
 [ 0  0  0  0  0  0  0  0  0  0 30  0  0  0  0  0  0  0  0  0  0  0]
 [ 0  0  0  0  0  0  1  0  0  0  0 29  0  0  0  0  0  0  0  0  0  0]
 [ 0  0  0  0  0  0  0  0  0  0  0  0 30  0  0  0  0  0  0  0  0  0]
 [ 0  1  0  0  0  0  0  0  0  0  0  0  0 29  0  0  0  0  0  0  0  0]
 [ 0  0  0  0  0  0  0  0  0  0  0  0  0  0 30  0  0  0  0  0  0  0]
```

```
[ 0  0  0  0  0  0  0  0  0  0  0  0  0  0  0 30  0  0  0  0  0  0]
[ 0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0 30  0  0  0  0  0]
[ 0  2  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0 28  0  0  0  0]
[ 0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0 30  0  0  0]
[ 0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0 30  0  0]
[ 0  1  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0 29  0]
[ 0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0 30]]
```

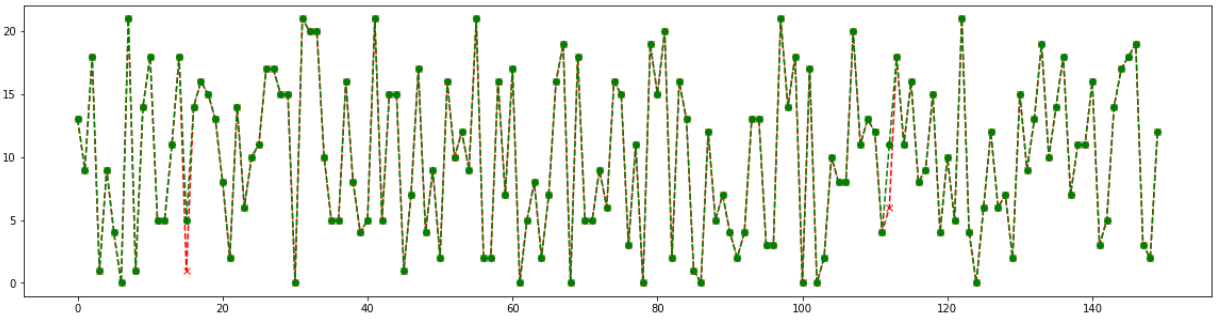
In [87]:

```
fig, ax = plt.subplots(figsize=(7,7))
plot_confusion_matrix(vot_clf, X_test, y_test, ax=ax)
plt.title('Confusion Matrix of Voting Classifier')
plt.show()
```



In [88]:

```
DF4 = p.DataFrame()
DF4["y_test"] = y_test
DF4["predicted"] = pred_vtng
DF4.reset_index(inplace=True)
plt.figure(figsize=(20, 5))
plt.plot(DF4["predicted"][:150], marker='x', linestyle='dashed', color='red')
plt.plot(DF4["y_test"][:150],  marker='o', linestyle='dashed', color='green')
plt.show()
```

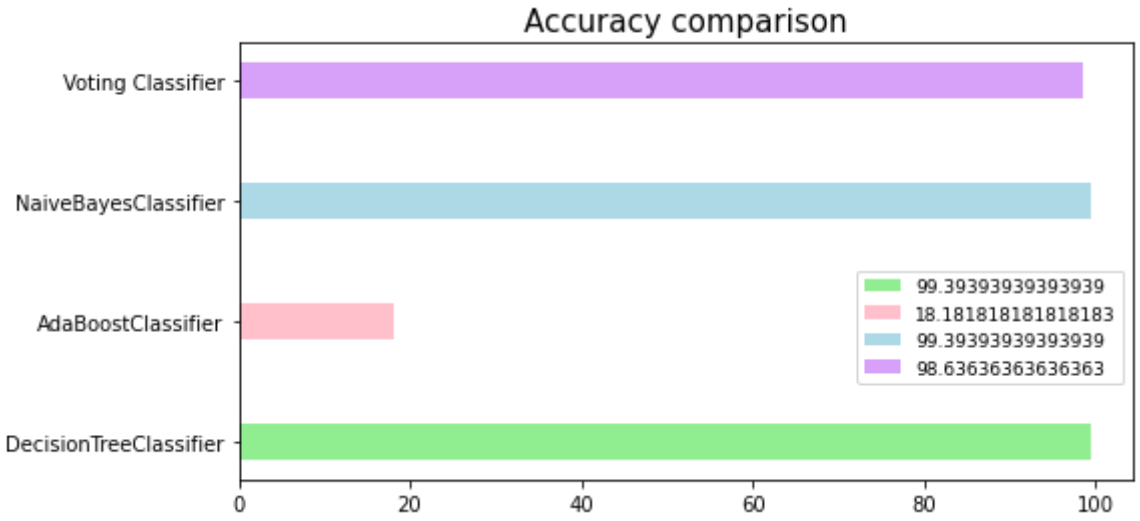


In [89]:

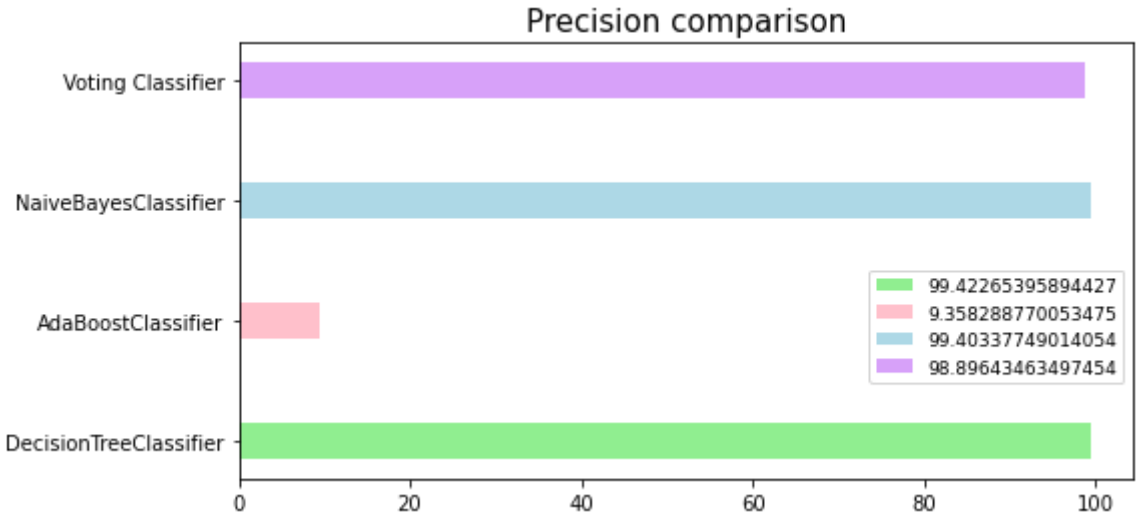
```
#Saving Model
joblib.dump(vot_clf,'vot_clf.pkl')
```

Out[89]:
```
['vot_clf.pkl']
```

In [90]:
```
def graph():
    data=[DT1,AB1,NB1,VC1]
    alg=["DecisionTreeClassifier","AdaBoostClassifier","NaiveBayesClassifier","Votin
    plt.figure(figsize=(8,4))
    b=plt.barh(alg,data,height=0.3, color=['lightgreen','pink','lightblue','#D7A1F9'
    plt.title("Accuracy comparison",fontsize=15)
    plt.legend(b,data,fontsize=9, bbox_to_anchor=(1.0, 0.5))
graph()
```

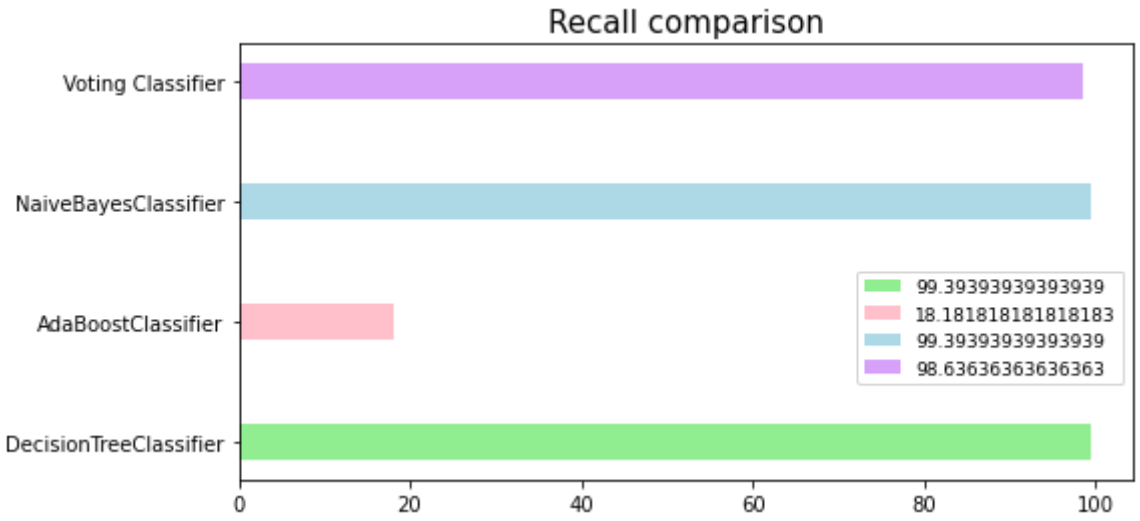


In [91]:
```
def graph():
    data=[DT2,AB2,NB2,VC2]
    alg=["DecisionTreeClassifier","AdaBoostClassifier","NaiveBayesClassifier","Votin
    plt.figure(figsize=(8,4))
    b=plt.barh(alg,data,height=0.3, color=['lightgreen','pink','lightblue','#D7A1F9'
    plt.title("Precision comparison",fontsize=15)
    plt.legend(b,data,fontsize=9,bbox_to_anchor=(1.0, 0.5))
graph()
```



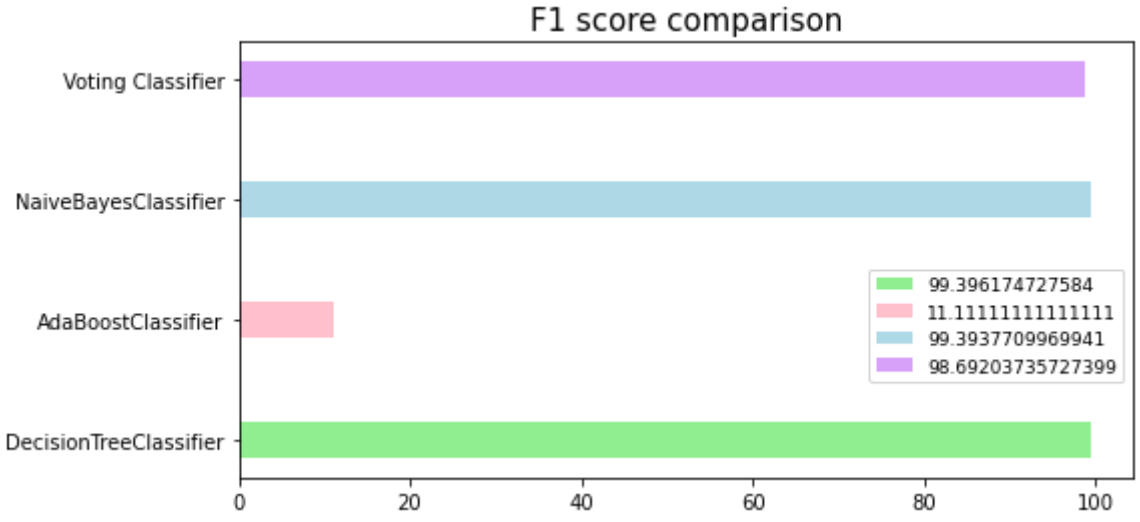
In [92]:
```
def graph():
    data=[DT3,AB3,NB3,VC3]
    alg=["DecisionTreeClassifier","AdaBoostClassifier","NaiveBayesClassifier","Votin
    plt.figure(figsize=(8,4))
    b=plt.barh(alg,data,height=0.3, color=['lightgreen','pink','lightblue','#D7A1F9'
    plt.title("Recall comparison",fontsize=15)
```

```
    plt.legend(b,data,fontsize=9,bbox_to_anchor=(1.0, 0.5))
graph()
```



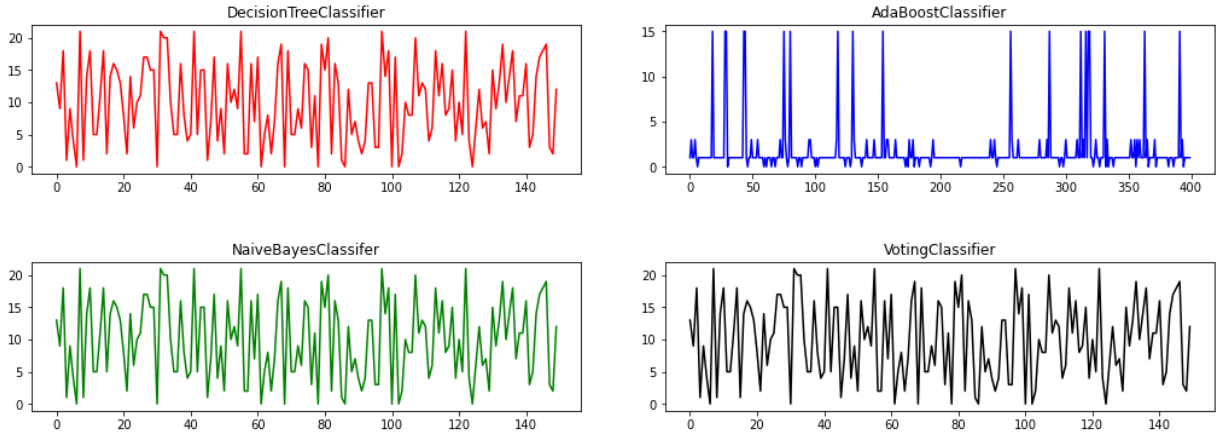
In [93]:

```
def graph():
    data=[DT4,AB4,NB4,VC4]
    alg=["DecisionTreeClassifier","AdaBoostClassifier","NaiveBayesClassifier","Votin
    plt.figure(figsize=(8,4))
    b=plt.barh(alg,data,height=0.3, color=['lightgreen','pink','lightblue','#D7A1F9'
    plt.title("F1 score comparison",fontsize=15)
    plt.legend(b,data,fontsize=9, bbox_to_anchor=(1.0, 0.5))
graph()
```



In [94]:

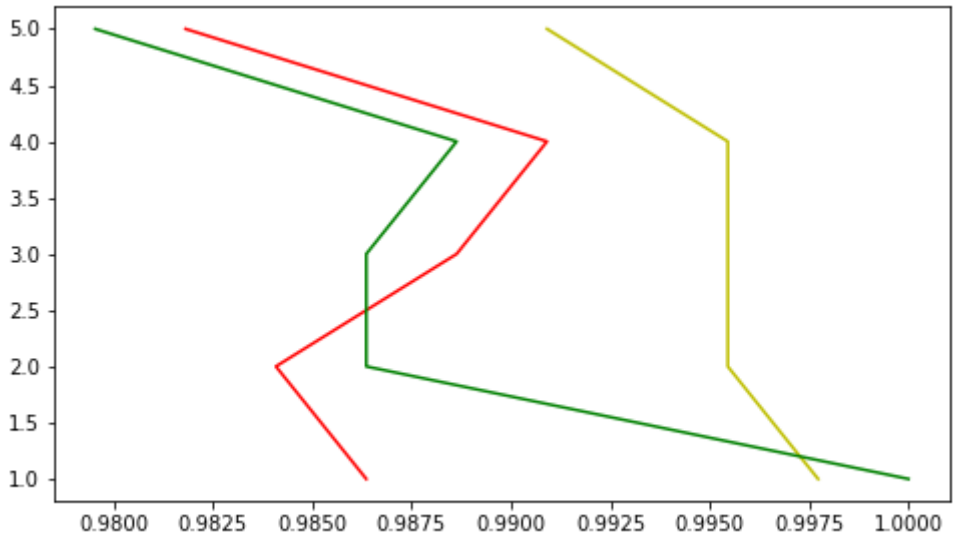
```
plt.figure(figsize=(15,6))
plt.subplot(2, 2, 1)
plt.title("DecisionTreeClassifier")
plt.plot(DF1["predicted"][:150],color='red')
plt.subplot(2,2,3)
plt.title("NaiveBayesClassifer")
plt.plot(DF2["predicted"][:150],color='green')
plt.subplot(2, 2, 2)
plt.title("AdaBoostClassifier")
plt.plot(DF3["predicted"][:400],color='blue')
plt.subplot(2,2,4)
plt.title("VotingClassifier")
plt.plot(DF4["predicted"][:150],color='black')
plt.tight_layout(4)
plt.show()
```

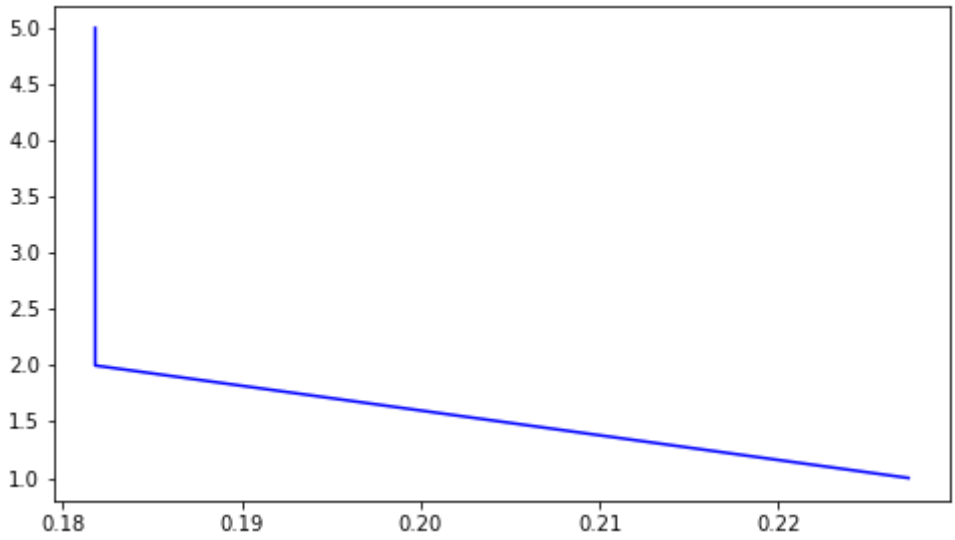


In [95]:
```
finalaccuracy_dt = cross_val_score(dt, inputs, output, scoring='accuracy')
print('Cross validation test results of accuracy of DecisionTreeClassifier:')
print(finalaccuracy_dt)
finalaccuracy_ab = cross_val_score(ab, inputs, output, scoring='accuracy')
print('Cross validation test results of accuracy of AdaBoostClassifier:')
print(finalaccuracy_ab)
finalaccuracy_nb = cross_val_score(nb, inputs, output, scoring='accuracy')
print('Cross validation test results of accuracy of NaiveBayesClassifier:')
print(finalaccuracy_nb)
finalaccuracy_vt = cross_val_score(vot_clf, inputs, output, scoring='accuracy')
print('Cross validation test results of accuracy of VotingClassifier:')
print(finalaccuracy_vt)
```

```
Cross validation test results of accuracy of DecisionTreeClassifier:
[0.98636364 0.98409091 0.98863636 0.99090909 0.98181818]
Cross validation test results of accuracy of AdaBoostClassifier:
[0.22727273 0.18181818 0.18181818 0.18181818 0.18181818]
Cross validation test results of accuracy of NaiveBayesClassifier:
[0.99772727 0.99545455 0.99545455 0.99545455 0.99090909]
Cross validation test results of accuracy of VotingClassifier:
[1.         0.98636364 0.98636364 0.98863636 0.97954545]
```

In [96]:
```
a=[1,2,3,4,5]
plt.figure(figsize=(8,10))
plt.subplot(2,1,1)
plt_d=plt.plot(finalaccuracy_dt, a, color = 'r')
#plt.legend(plt_d,"DecisionTreeClassifier",fontsize=9,loc='center left', bbox_to_anc
plt_n=plt.plot(finalaccuracy_nb, a, color = 'y')
#plt.legend(plt_n,"NaiveBayesClassifier",fontsize=9,loc='center left', bbox_to_ancho
plt_v=plt.plot(finalaccuracy_vt, a, color = 'g')
plt.subplot(2,1,2)
plt_a=plt.plot(finalaccuracy_ab, a, color = 'b')
plt_arr=[plt_d,plt_n,plt_v,plt_a]
n_arr=["DecisionTreeClassifier","NaiveBayesClassifier","VotingClassifier","AdaBoostC
plt.show()
```


5.0
4.5
4.0
3.5
3.0
2.5
2.0
1.5
1.0
0.9800
0.9825
0.9850
0.9875
0.9900
0.9925
0.9950
0.9975
1.0000


5.0
4.5
4.0
3.5
3.0
2.5
2.0
1.5
1.0
0.18
0.19
0.20
0.21
0.22