Seleção de Modelos & Métricas de avaliação

1 - Bibliotecas, Datasets e Funções de Plotagem

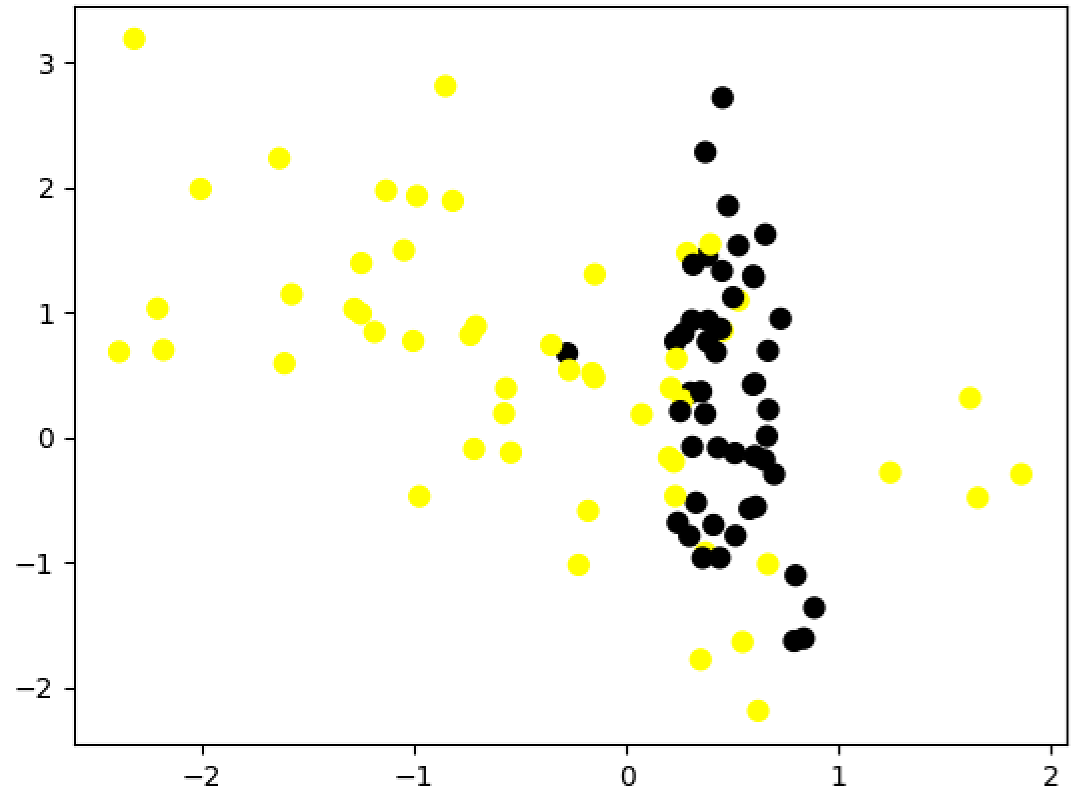
In [2]:

```
# libs

%matplotlib notebook
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt

import matplotlib.patches as mpatches
from matplotlib.colors import ListedColormap
from sklearn.model_selection import train_test_split
from sklearn.datasets import make_classification, make_blobs
from sklearn.datasets import load_digits

cmap_bold = ListedColormap(['#FFFF00', '#00FF00', '#0000FF','#000000'])
```

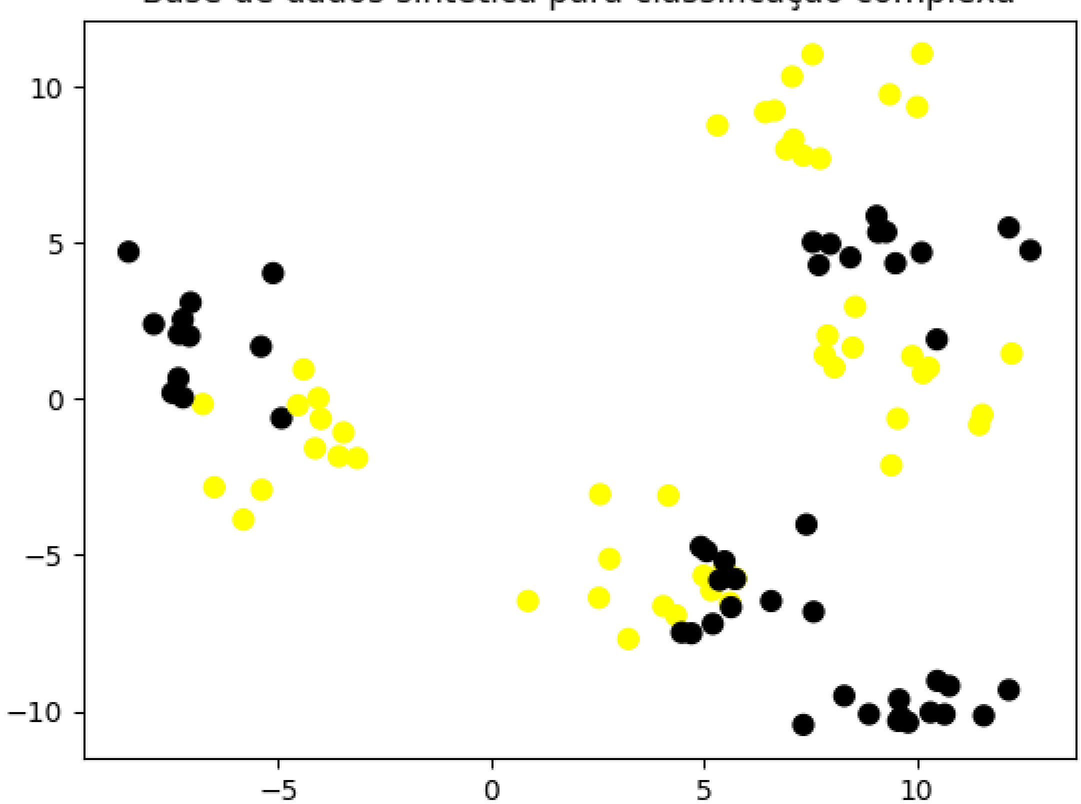
In [3]:

```
# Base de Dados Frutas
fruits = pd.read_table('./Data/fruit_data_with_colors.txt')

feature_names_fruits = ['height', 'width', 'mass', 'color_score']
X_fruits = fruits[feature_names_fruits]
y_fruits = fruits['fruit_label']
target_names_fruits = ['apple', 'mandarin', 'orange', 'lemon']

X_fruits_2d = fruits[['height', 'width']]
y_fruits_2d = fruits['fruit_label']

X_train, X_test, y_train, y_test = train_test_split(X_fruits, y_fruits, random_state=0)


# Base de dados sintética para classificação binária simples
plt.figure()
plt.title('Base de dados sintética para classificação binária simples')
X_C2, y_C2 = make_classification(n_samples = 100, n_features=2,
                                n_redundant=0, n_informative=2,
                                n_clusters_per_class=1, flip_y = 0.1,
                                class_sep = 0.5, random_state=0)
plt.scatter(X_C2[:, 0], X_C2[:, 1], c=y_C2,
           marker= 'o', s=50, cmap=cmap_bold)
plt.show()


# Base de dados sintética para classificação complexa
X_D2, y_D2 = make_blobs(n_samples = 100, n_features = 2, centers = 8,
                       cluster_std = 1.3, random_state = 4)
y_D2 = y_D2 % 2
plt.figure()
plt.title('Base de dados sintética para classificação complexa')
plt.scatter(X_D2[:,0], X_D2[:,1], c=y_D2,
           marker= 'o', s=50, cmap=cmap_bold)
plt.show()
```

Base de dados sintética para classificação binária simples



Base de dados sintética para classificação complexa



In [5]:

```
#Funções de Plotagem
```

```
def plot_class_regions_for_classifier_subplot(clf, X, y,
                                              X_test, y_test,
                                              title, subplot,
                                              target_names = None,
                                              plot_decision_regions = True):

    numClasses = np.amax(y) + 1
    color_list_light = ['#FFFFAA', '#EFEFEF', '#AAFFAA', '#AAAAFF']
    color_list_bold = ['#EEEE00', '#000000', '#00CC00', '#0000CC']
    cmap_light = ListedColormap(color_list_light[0:numClasses])
    cmap_bold  = ListedColormap(color_list_bold[0:numClasses])

    h = 0.03
    k = 0.5
    x_plot_adjust = 0.1
    y_plot_adjust = 0.1
    plot_symbol_size = 50

    x_min = X[:, 0].min()
    x_max = X[:, 0].max()
    y_min = X[:, 1].min()
    y_max = X[:, 1].max()
    x2, y2 = np.meshgrid(np.arange(x_min-k, x_max+k, h), np.arange(y_min-k, y_max+k, h))

    P = clf.predict(np.c_[x2.ravel(), y2.ravel()])
    P = P.reshape(x2.shape)

    if plot_decision_regions:
        subplot.contourf(x2, y2, P, cmap=cmap_light, alpha = 0.8)

    subplot.scatter(X[:, 0], X[:, 1], c=y, cmap=cmap_bold, s=plot_symbol_size, edgecolor =
    subplot.set_xlim(x_min - x_plot_adjust, x_max + x_plot_adjust)
    subplot.set_ylim(y_min - y_plot_adjust, y_max + y_plot_adjust)

    if (X_test is not None):
        subplot.scatter(X_test[:, 0], X_test[:, 1], c=y_test, cmap=cmap_bold, s=plot_symbo
        train_score = clf.score(X, y)
        test_score  = clf.score(X_test, y_test)
        title = title + "\nTreinamento = {:.2f}, Teste = {:.2f}".format(train_score, test_

    subplot.set_title(title)

    if (target_names is not None):
        legend_handles = []
        for i in range(0, len(target_names)):
            patch = mpatches.Patch(color=color_list_bold[i], label=target_names[i])
            legend_handles.append(patch)
        subplot.legend(loc=0, handles=legend_handles)


def plot_class_regions_for_classifier(clf, X, y,
                                      X_test=None, y_test=None,
                                      title=None,
                                      target_names = None,
                                      plot_decision_regions = True):

    numClasses = np.amax(y) + 1
    color_list_light = ['#FFFFAA', '#EFEFEF', '#AAFFAA', '#AAAAFF']
    color_list_bold = ['#EEEE00', '#000000', '#00CC00', '#0000CC']
    cmap_light = ListedColormap(color_list_light[0:numClasses])
    cmap_bold  = ListedColormap(color_list_bold[0:numClasses])

    h = 0.03
    k = 0.5
    x_plot_adjust = 0.1
    y_plot_adjust = 0.1
```

```
    plot_symbol_size = 50

    x_min = X[:, 0].min()
    x_max = X[:, 0].max()
    y_min = X[:, 1].min()
    y_max = X[:, 1].max()
    x2, y2 = np.meshgrid(np.arange(x_min-k, x_max+k, h), np.arange(y_min-k, y_max+k, h))

    P = clf.predict(np.c_[x2.ravel(), y2.ravel()])
    P = P.reshape(x2.shape)
    plt.figure()
    if plot_decision_regions:
        plt.contourf(x2, y2, P, cmap=cmap_light, alpha = 0.8)

    plt.scatter(X[:, 0], X[:, 1], c=y, cmap=cmap_bold, s=plot_symbol_size, edgecolor = 'bl
    plt.xlim(x_min - x_plot_adjust, x_max + x_plot_adjust)
    plt.ylim(y_min - y_plot_adjust, y_max + y_plot_adjust)

    if (X_test is not None):
        plt.scatter(X_test[:, 0], X_test[:, 1], c=y_test, cmap=cmap_bold, s=plot_symbol_si
        train_score = clf.score(X, y)
        test_score  = clf.score(X_test, y_test)
        title = title + "\nTreinamento = {:.2f}, Teste = {:.2f}".format(train_score, test_

    if (target_names is not None):
        legend_handles = []
        for i in range(0, len(target_names)):
            patch = mpatches.Patch(color=color_list_bold[i], label=target_names[i])
            legend_handles.append(patch)
        plt.legend(loc=0, handles=legend_handles)

    if (title is not None):
        plt.title(title)
    plt.show()
```

2 - Exemplo de Validação Cruzada

In [6]:

```
from sklearn.model_selection import cross_val_score
from sklearn.svm import SVC

dataset = load_digits()

X, y = dataset.data, dataset.target == 1
clf = SVC(kernel='linear', C=1)

print('Acurácia', cross_val_score(clf, X, y, cv=5))
print('AUC', cross_val_score(clf, X, y, cv=5, scoring = 'roc_auc'))
print('Recall', cross_val_score(clf, X, y, cv=5, scoring = 'recall'))
```

```
Acurácia [0.91944444 0.98611111 0.97214485 0.97493036 0.96935933]
AUC [0.9641871  0.9976571  0.99372205 0.99699002 0.98675611]
Recall [0.81081081 0.89189189 0.83333333 0.83333333 0.83333333]
```

3 - Exemplo de GridSearch

In [8]:

```
from sklearn.svm import SVC
from sklearn.model_selection import GridSearchCV
from sklearn.metrics import roc_auc_score

dataset = load_digits()
X, y = dataset.data, dataset.target == 1
X_train, X_test, y_train, y_test = train_test_split(X, y, random_state=0)
```

```python
clf = SVC(kernel='rbf')
grid_values = {'gamma': [0.001, 0.01, 0.05, 0.1, 1, 10, 100]}

# Acurácia é o Padrão
grid_clf_acc = GridSearchCV(clf, param_grid = grid_values)
grid_clf_acc.fit(X_train, y_train)
y_decision_fn_scores_acc = grid_clf_acc.decision_function(X_test)

print('Melhor parâmetro (max. acurácia): ', grid_clf_acc.best_params_)
print('Melhor escore (acurácia): ', grid_clf_acc.best_score_)
print()

# AUC
grid_clf_auc = GridSearchCV(clf, param_grid = grid_values, scoring = 'roc_auc')
grid_clf_auc.fit(X_train, y_train)
y_decision_fn_scores_auc = grid_clf_auc.decision_function(X_test)
# roc_auc_score?

print('Conjunto de teste AUC: ', roc_auc_score(y_test, y_decision_fn_scores_auc))
print('Melhor parâmetro (max. AUC): ', grid_clf_auc.best_params_)
print('Melhor escore (AUC): ', grid_clf_auc.best_score_)
```

```
Melhor parâmetro (max. acurácia):  {'gamma': 0.001}
Melhor escore (acurácia):  0.9985157648354676

Conjunto de teste AUC:  0.99982858122393
Melhor parâmetro (max. AUC):  {'gamma': 0.001}
Melhor escore (AUC):  1.0
```

4 - Lista completa das métricas de avaliação suportadas pelo sklearn.

In [19]:

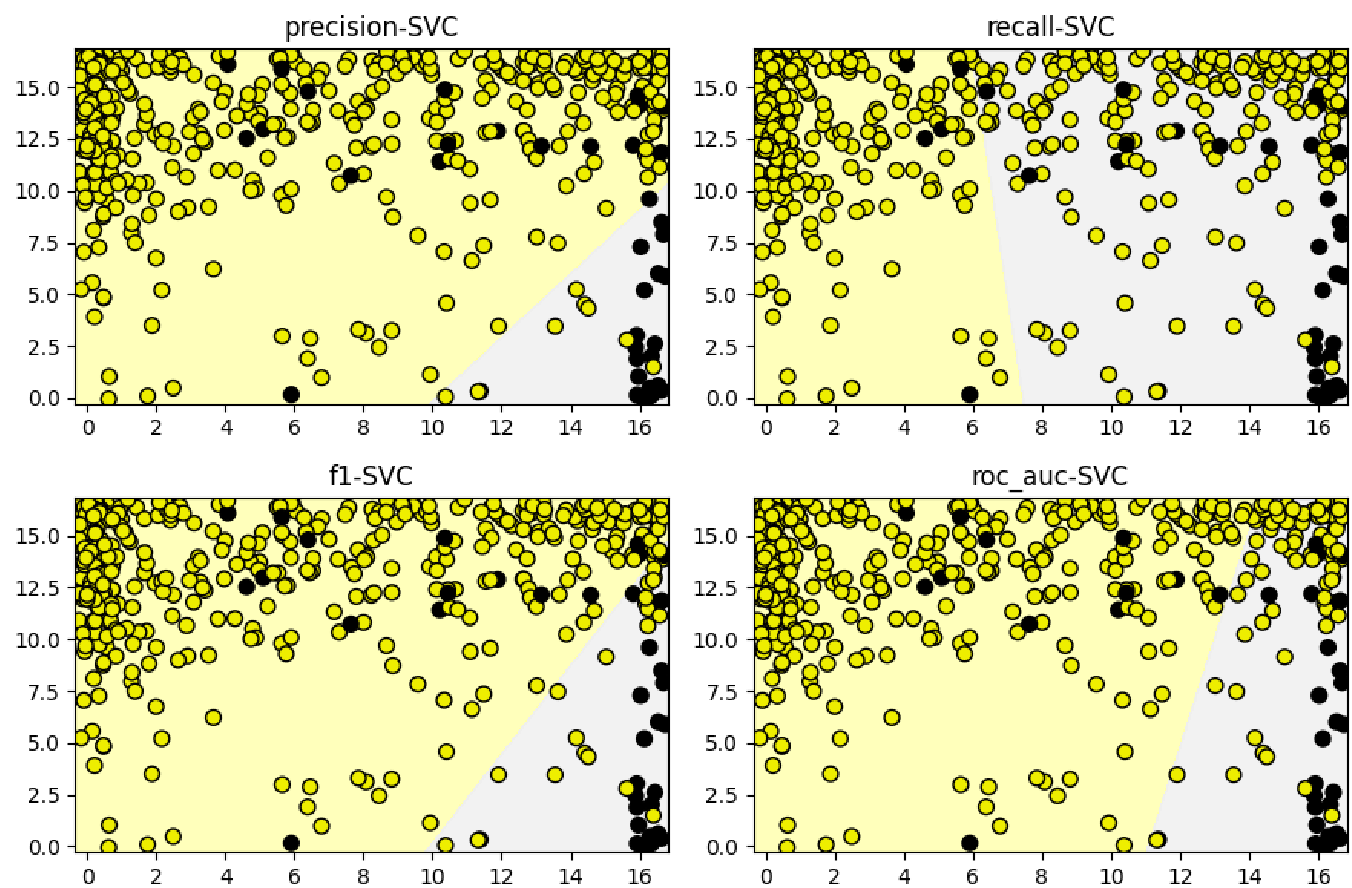
```python
# from sklearn.metrics.scorer import SCORERS

# print(sorted(list(SCORERS.keys())))
```

5 - Otimizando o classificador usando métricas de desempenho diferentes

In [25]:

```python
from sklearn.datasets import load_digits
from sklearn.model_selection import GridSearchCV

dataset = load_digits()
X, y = dataset.data, dataset.target == 1
X_train, X_test, y_train, y_test = train_test_split(X, y, random_state=0)

jitter_delta = 0.25
X_twovar_train = X_train[:,[20,59]] + np.random.rand(X_train.shape[0], 2) - jitter_delta
X_twovar_test  = X_test[:,[20,59]] + np.random.rand(X_test.shape[0], 2) - jitter_delta

clf = SVC(kernel = 'linear').fit(X_twovar_train, y_train)
grid_values = {'class_weight':['balanced', {1:2},{1:3},{1:4},{1:5},{1:10},{1:20},{1:50}]}

plt.figure(figsize=(9,6))
for i, eval_metric in enumerate(('precision','recall', 'f1','roc_auc')):
    grid_clf_custom = GridSearchCV(clf, param_grid=grid_values, scoring=eval_metric)
    grid_clf_custom.fit(X_twovar_train, y_train)
    print('Melhor parâmetro (max. {0}): {1}'.format(eval_metric, grid_clf_custom.best_para
    print('Melhor escore ({0}): {1}\n'.format(eval_metric, grid_clf_custom.best_score_))
    plt.subplots_adjust(wspace=0.3, hspace=0.3)
    plot_class_regions_for_classifier_subplot(grid_clf_custom, X_twovar_test, y_test, None
                                             None, None,  plt.subplot(2, 2, i+1))

    plt.title(eval_metric+'-SVC')
```

```
plt.tight_layout()
plt.show()
```



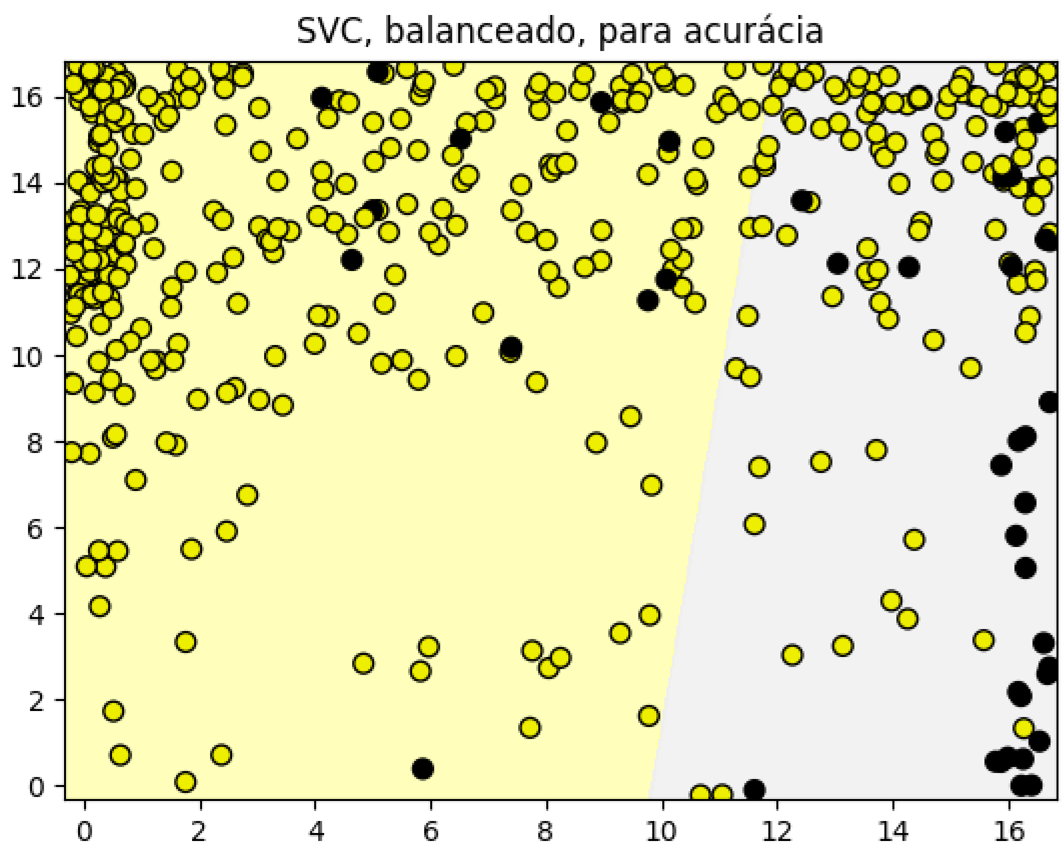

```
Melhor parâmetro (max. precision): {'class_weight': {1: 2}}
Melhor escore (precision): 0.530690537084399

Melhor parâmetro (max. recall): {'class_weight': {1: 50}}
Melhor escore (recall): 0.9285714285714285

Melhor parâmetro (max. f1): {'class_weight': {1: 3}}
Melhor escore (f1): 0.5520959490283193

Melhor parâmetro (max. roc_auc): {'class_weight': {1: 4}}
Melhor escore (roc_auc): 0.8932829126529617
```

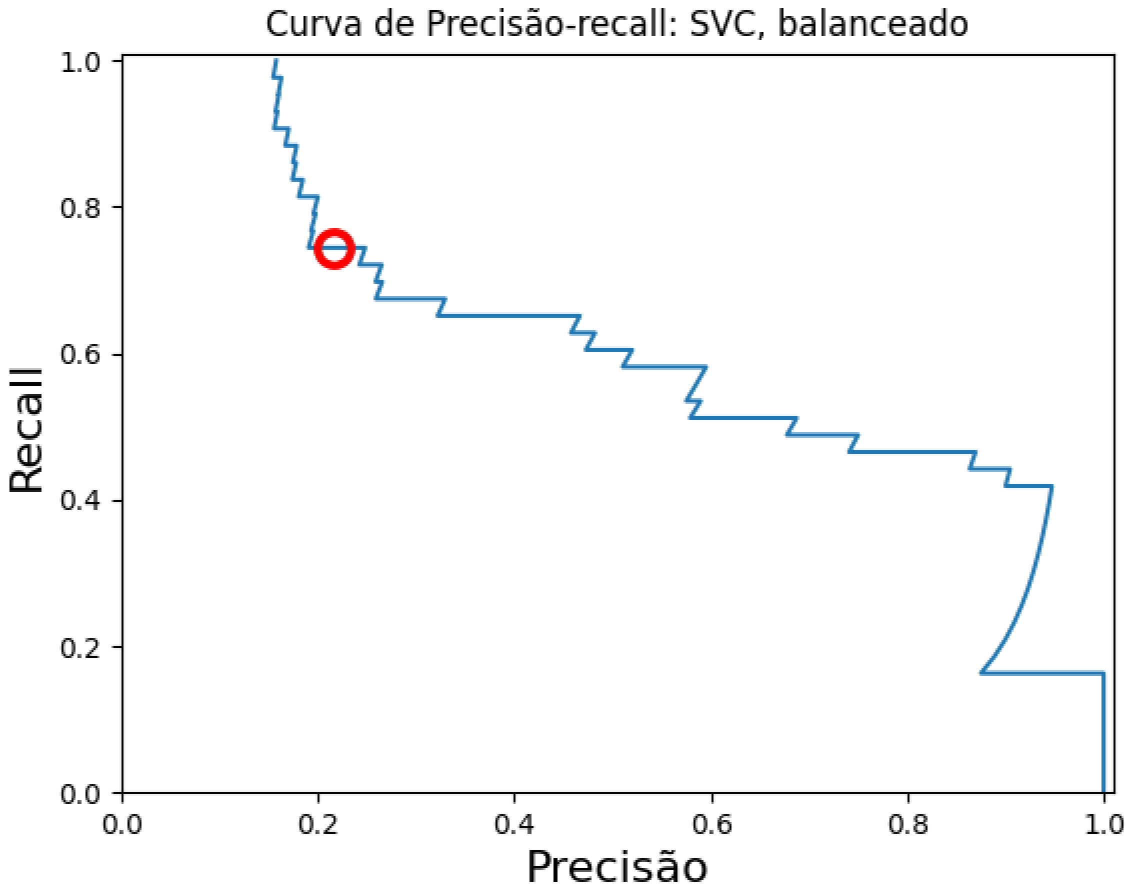
6 - Curva de precisão-recall para classificador SVC - pesos de classe balanceados

In [27]:

```
from sklearn.metrics import precision_recall_curve

dataset = load_digits()
X, y = dataset.data, dataset.target == 1
X_train, X_test, y_train, y_test = train_test_split(X, y, random_state=0)

jitter_delta = 0.25
X_twovar_train = X_train[:,[20,59]]+ np.random.rand(X_train.shape[0], 2) - jitter_delta
X_twovar_test  = X_test[:,[20,59]] + np.random.rand(X_test.shape[0], 2) - jitter_delta

clf = SVC(kernel='linear', class_weight='balanced').fit(X_twovar_train, y_train)

y_scores = clf.decision_function(X_twovar_test)

precision, recall, thresholds = precision_recall_curve(y_test, y_scores)
closest_zero = np.argmin(np.abs(thresholds))
closest_zero_p = precision[closest_zero]
```

```
closest_zero_r = recall[closest_zero]

plot_class_regions_for_classifier(clf, X_twovar_test, y_test)
plt.title("SVC, balanceado, para acurácia")
plt.show()

plt.figure()
plt.xlim([0.0, 1.01])
plt.ylim([0.0, 1.01])
plt.title ("Curva de Precisão-recall: SVC, balanceado")
plt.plot(precision, recall, label = 'Curva de Precisão-recall')
plt.plot(closest_zero_p, closest_zero_r, 'o', markersize=12, fillstyle='none', c='r', mew=
plt.xlabel('Precisão', fontsize=16)
plt.ylabel('Recall', fontsize=16)
# plt.axes().set_aspect('equal')
plt.show()
print('No zero, precisão: {:.2f}, recall: {:.2f}'.format(closest_zero_p, closest_zero_r))
```





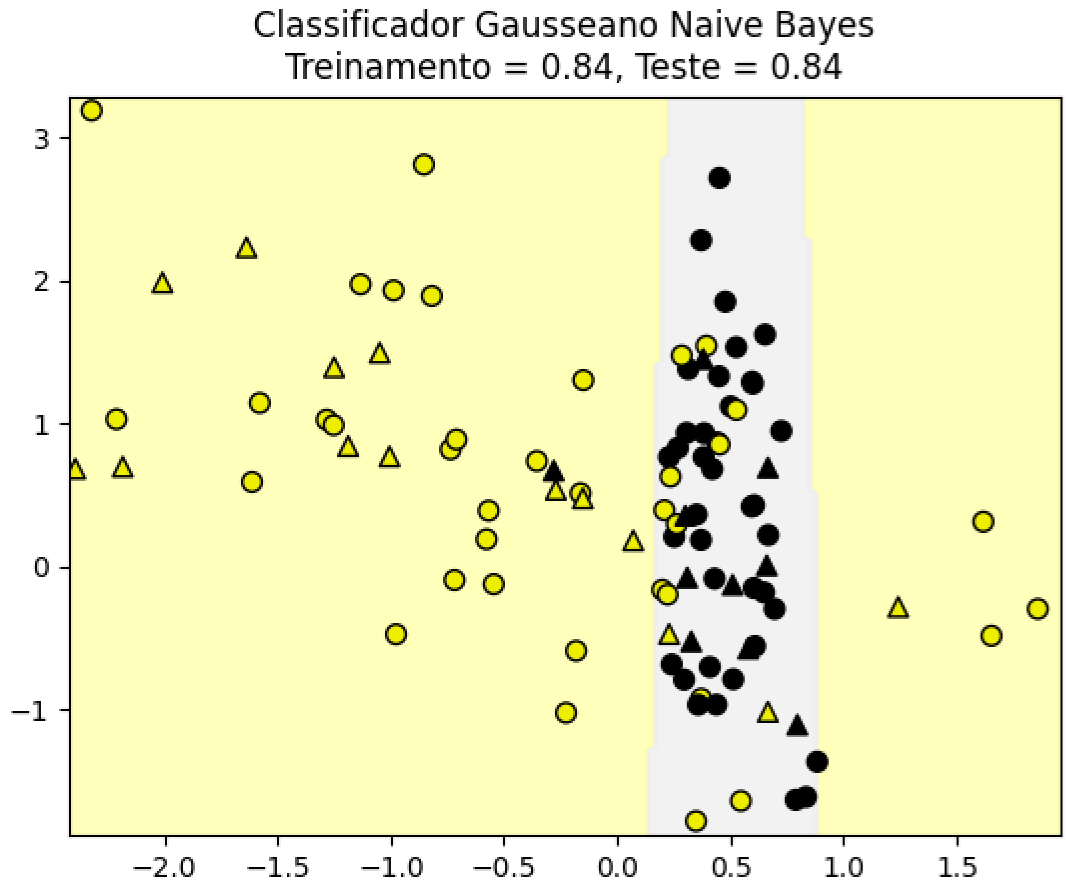

```
No zero, precisão: 0.22, recall: 0.74
```

Classificadores Naive Bayes

7 - Exemplo de classificador Gaussiano Naive Bayes

In [28]:

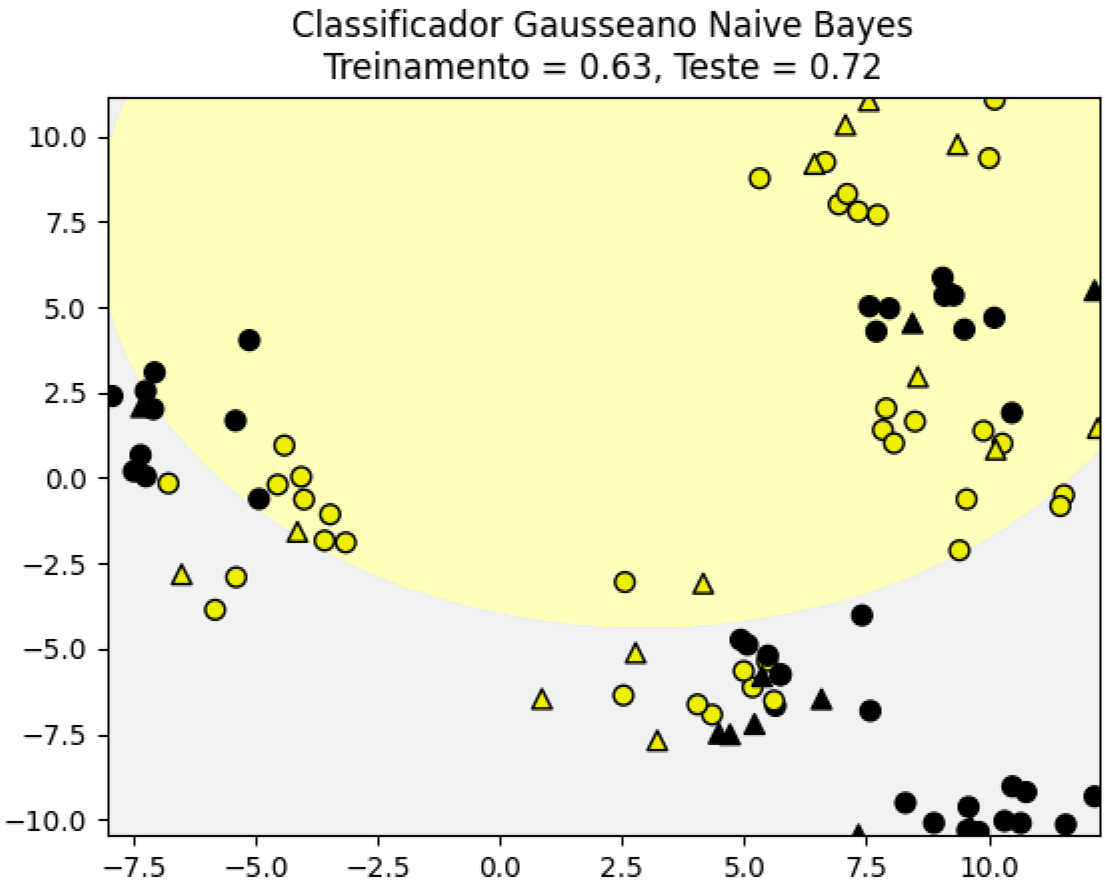
```
from sklearn.naive_bayes import GaussianNB

X_train, X_test, y_train, y_test = train_test_split(X_C2, y_C2, random_state=0)

nbclf = GaussianNB().fit(X_train, y_train)
plot_class_regions_for_classifier(nbclf, X_train, y_train, X_test, y_test,
                                   'Classificador Gausseano Naive Bayes')
```



8 - Exemplo de classificador Gaussiano Naive Bayes em uma base de dados complexa

In [29]:

```
X_train, X_test, y_train, y_test = train_test_split(X_D2, y_D2,
                                                   random_state=0)

nbclf = GaussianNB().fit(X_train, y_train)
plot_class_regions_for_classifier(nbclf, X_train, y_train, X_test, y_test,
                                 'Classificador Gausseano Naive Bayes')
```

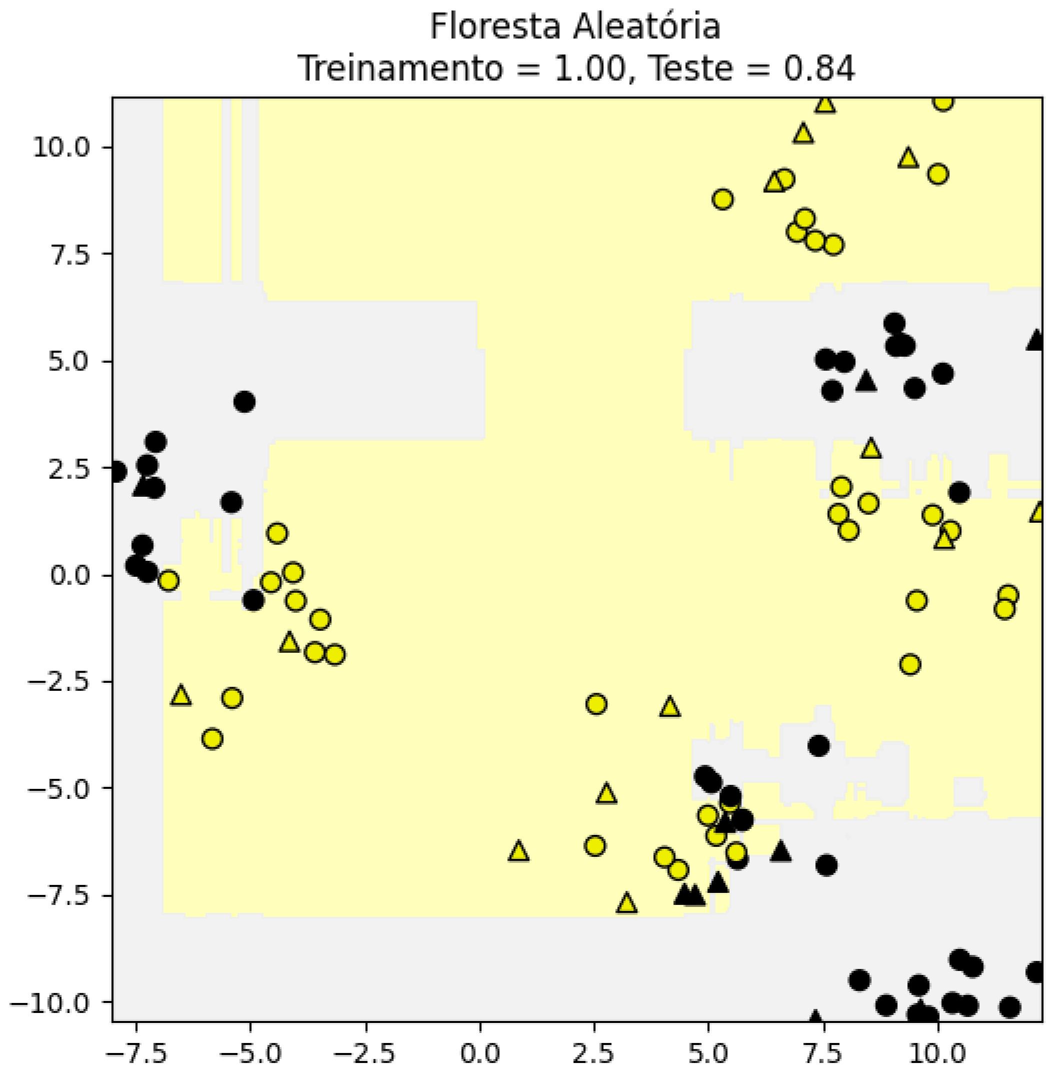


Conjuntos de árvores de decisão

8 - Florestas Aleatórias

In [31]:

```
from sklearn.ensemble import RandomForestClassifier

X_train, X_test, y_train, y_test = train_test_split(X_D2, y_D2, random_state = 0)
fig, subaxes = plt.subplots(1, 1, figsize=(6, 6))

clf = RandomForestClassifier().fit(X_train, y_train)

title = 'Floresta Aleatória'
plot_class_regions_for_classifier_subplot(clf, X_train, y_train, X_test,y_test, title, sub

plt.show()
```

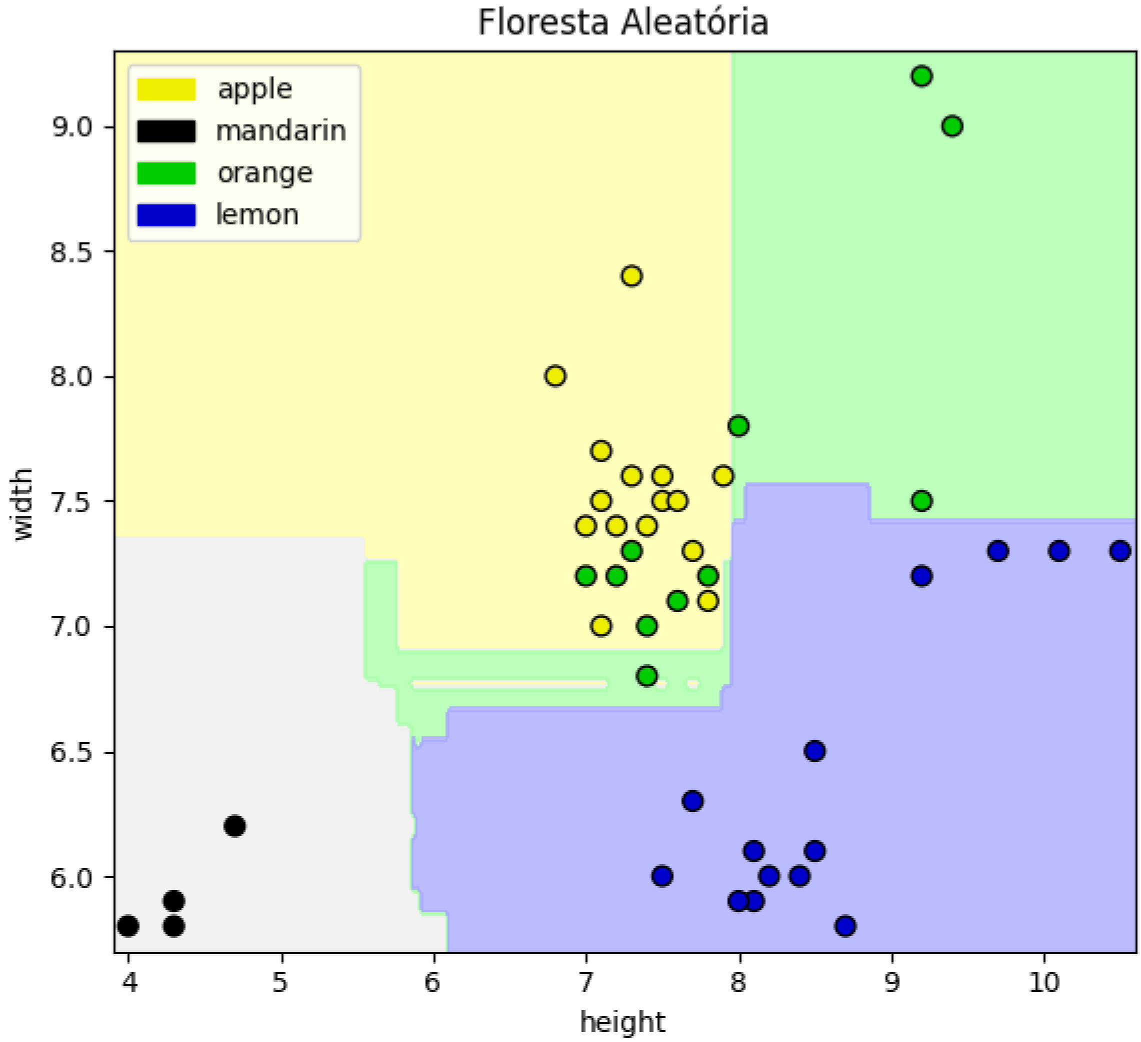


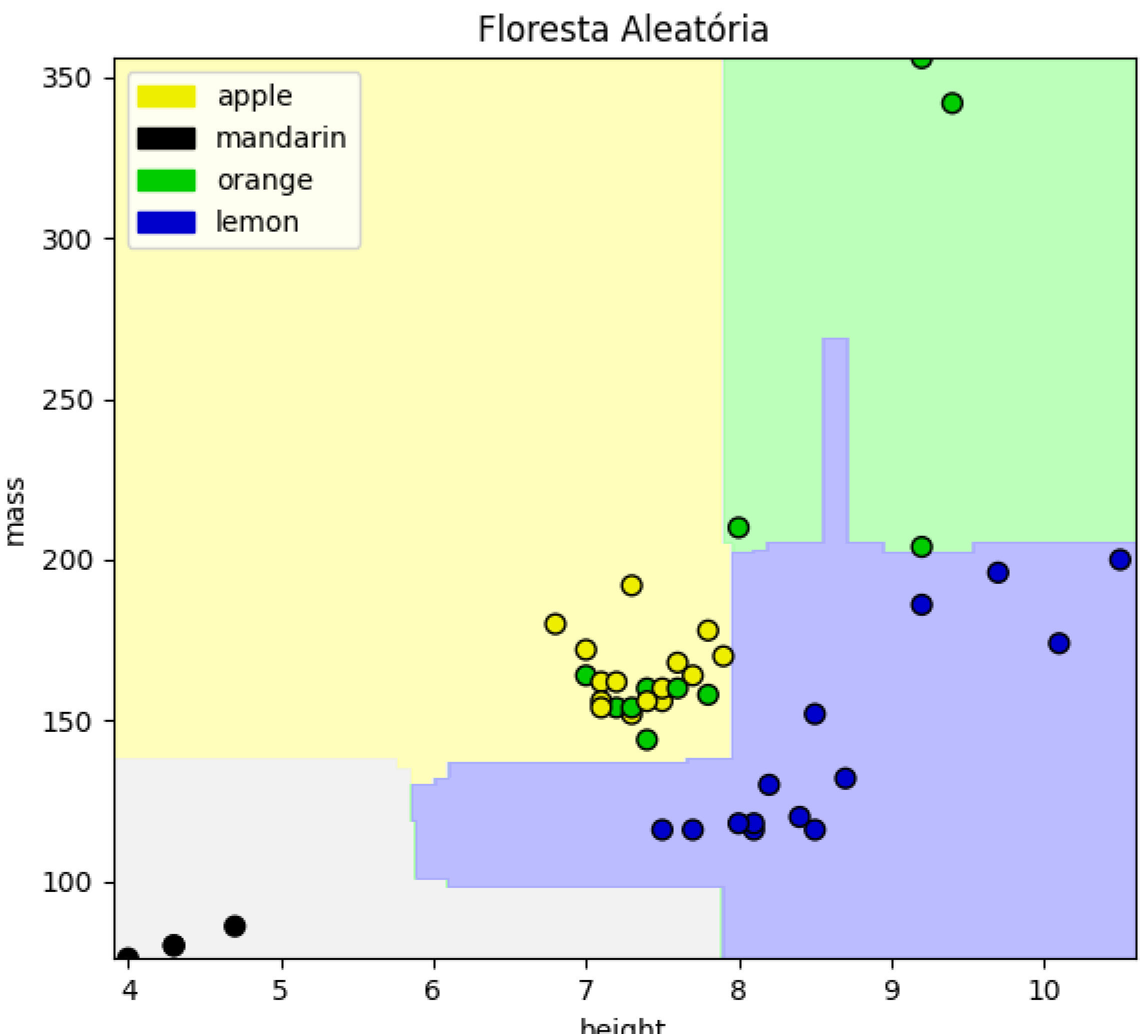
9 - Floresta aleatória na base de dados frutas

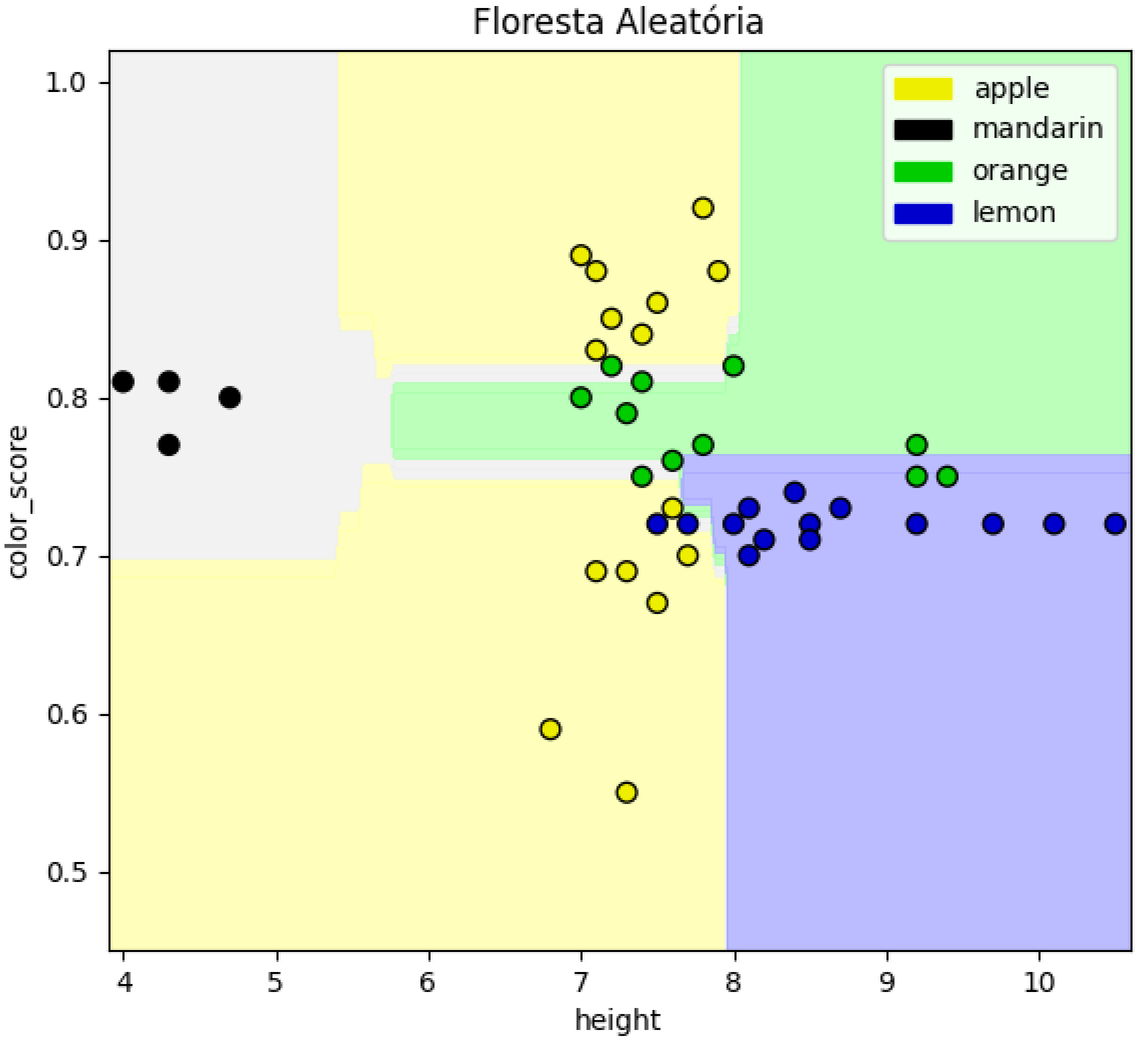
In [32]:

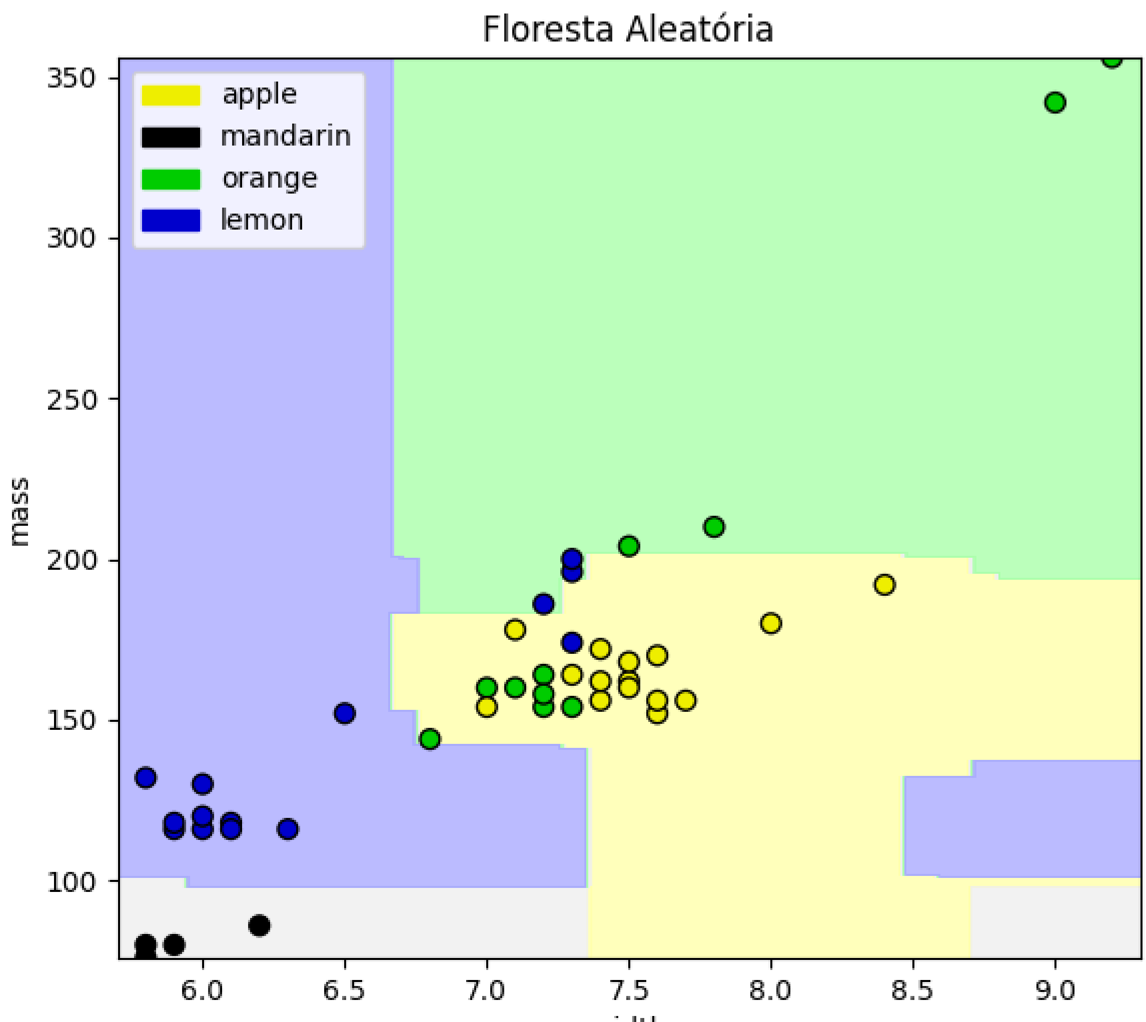
```
from sklearn.ensemble import RandomForestClassifier

X_train, X_test, y_train, y_test = train_test_split(X_fruits.to_numpy(), y_fruits.to_numpy

fig, subaxes = plt.subplots(6, 1, figsize=(6, 32))
title = 'Floresta Aleatória'

pair_list = [[0,1], [0,2], [0,3], [1,2], [1,3], [2,3]]
for pair, axis in zip(pair_list, subaxes):
    X = X_train[:, pair]
    y = y_train

    clf = RandomForestClassifier(n_jobs=8, max_depth = 2).fit(X, y)
    plot_class_regions_for_classifier_subplot(clf, X, y, None,
                                              None, title, axis,
                                              target_names_fruits)

    axis.set_xlabel(feature_names_fruits[pair[0]])
    axis.set_ylabel(feature_names_fruits[pair[1]])

plt.tight_layout()
plt.show()

clf = RandomForestClassifier(n_estimators = 10, random_state=0).fit(X_train, y_train)
```

```
print('Acurácia no treinamento: {:.2f}'.format(clf.score(X_train, y_train)))
print('Acurácia no teste: {:.2f}'.format(clf.score(X_test, y_test)))
```

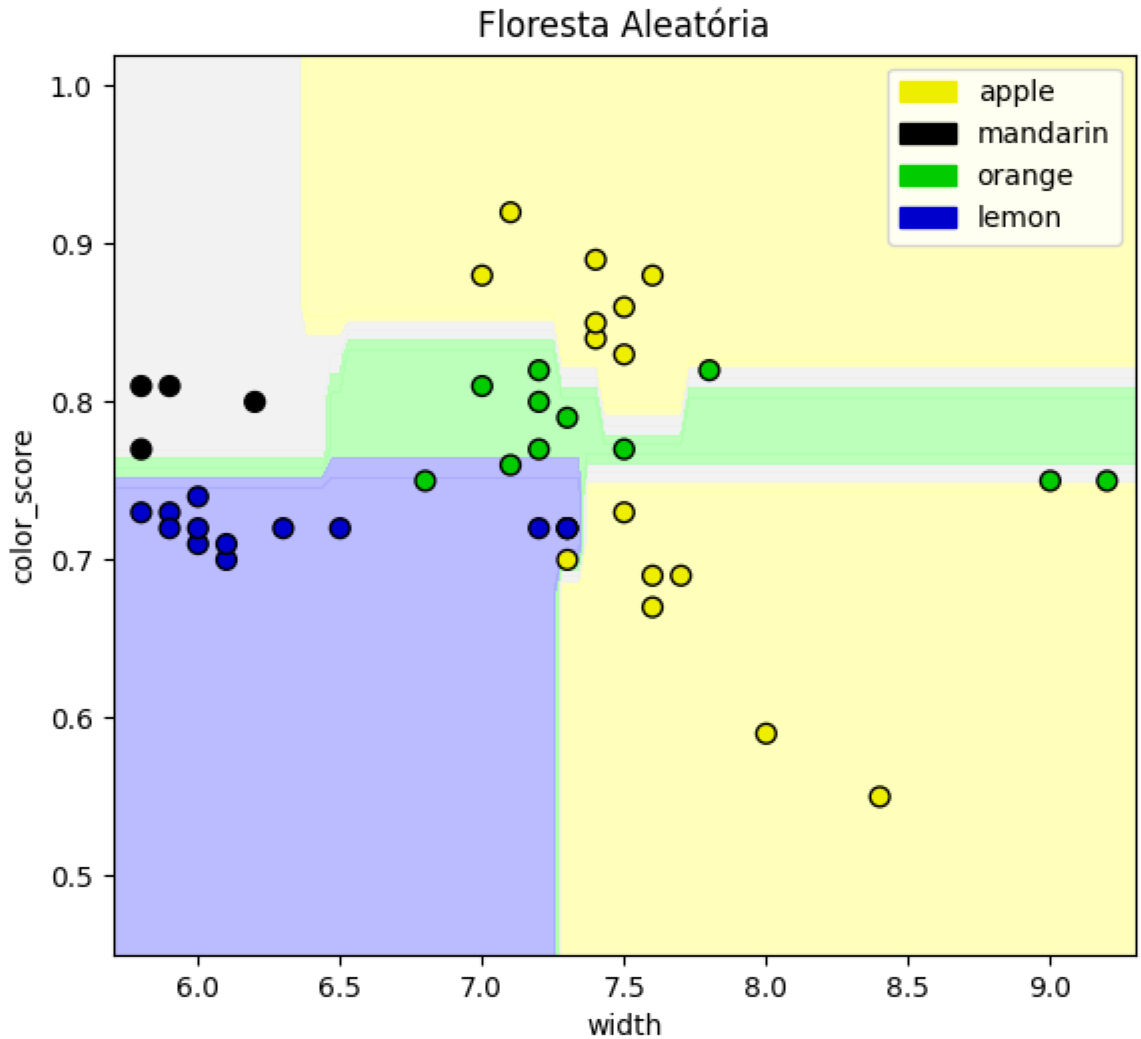

Floresta Aleatória
apple
mandarin
orange
lemon
width
height
9.0
8.5
8.0
7.5
7.0
6.5
6.0
4
5
6
7
8
9
10

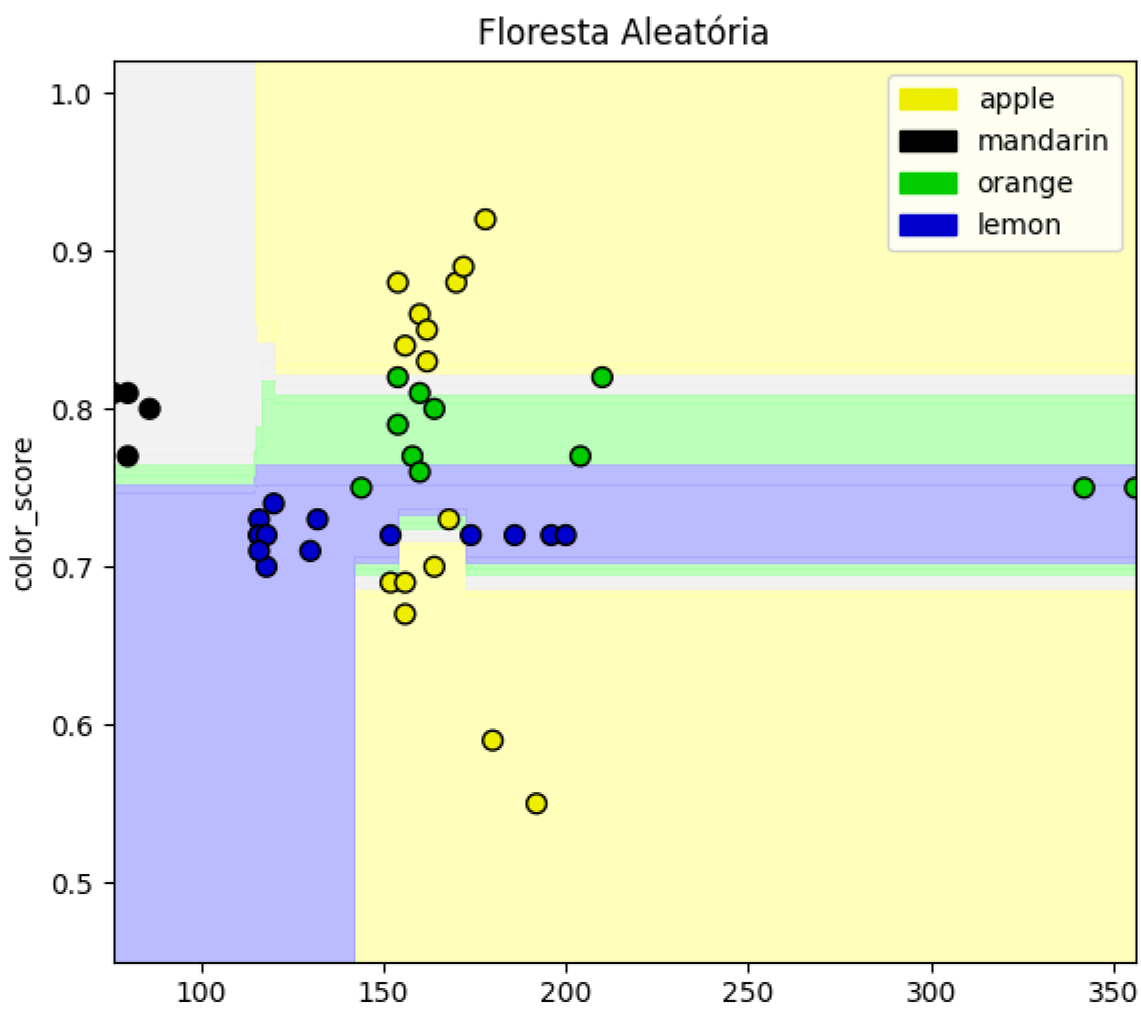

Floresta Aleatória
apple
mandarin
orange
lemon
mass
height
350
300
250
200
150
100
4
5
6
7
8
9
10


Floresta Aleatória
apple
mandarin
orange
lemon
color_score
1.0
0.9
0.8
0.7
0.6
0.5
4
5
6
7
8
9
10
height


Floresta Aleatória
apple
mandarin
orange
lemon
mass
350
300
250
200
150
100
6.0
6.5
7.0
7.5
8.0
8.5
9.0

width


Floresta Aleatória
apple
mandarin
orange
lemon
color_score
width
1.0
0.9
0.8
0.7
0.6
0.5
6.0
6.5
7.0
7.5
8.0
8.5
9.0


Floresta Aleatória
apple
mandarin
orange
lemon
color_score
1.0
0.9
0.8
0.7
0.6
0.5
100
150
200
250
300
350

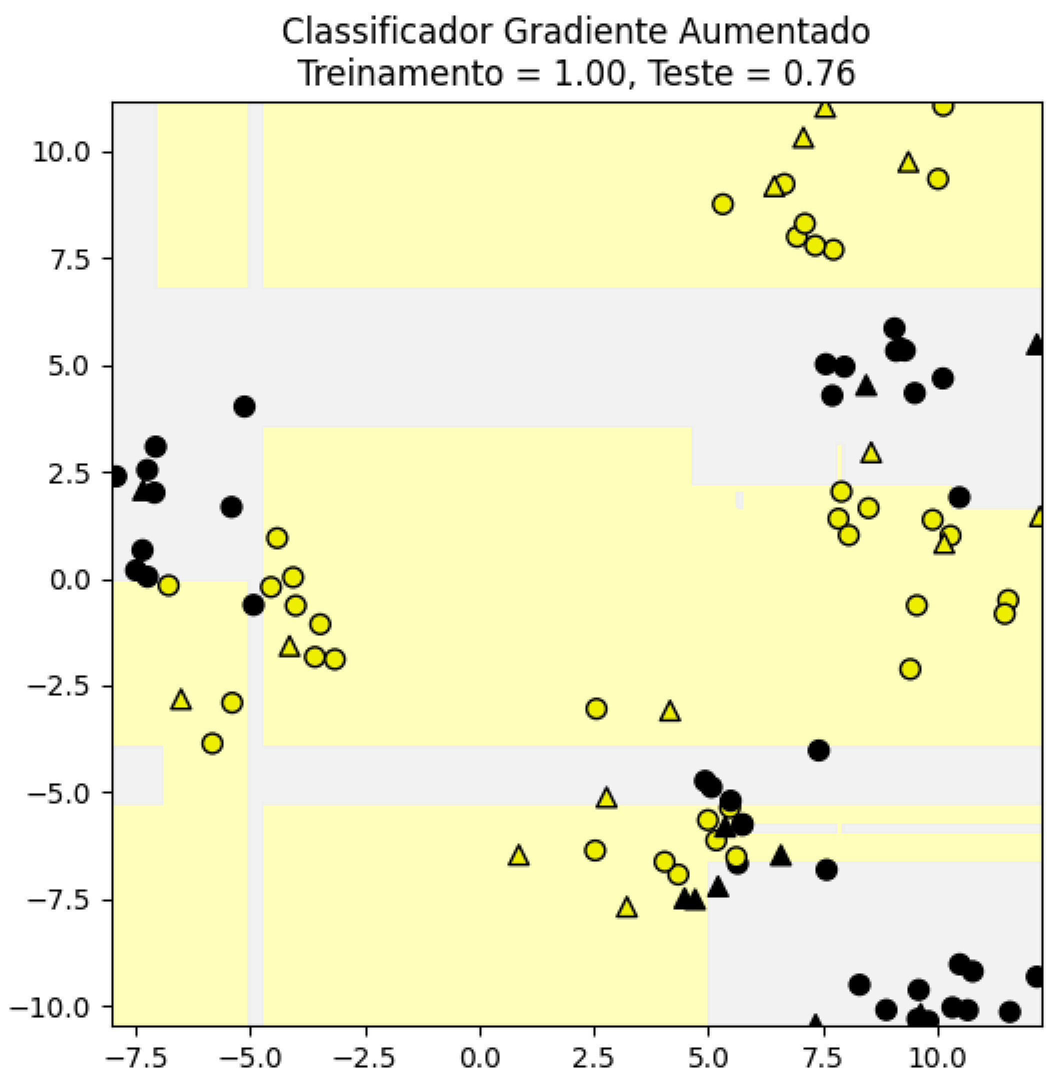
mass

```
Acurácia no treinamento: 1.00
Acurácia no teste: 0.80
```

10 - Árvores de decisão com o gradiente aumentado (Gradient-boosted)

In [33]:

```python
from sklearn.ensemble import GradientBoostingClassifier

X_train, X_test, y_train, y_test = train_test_split(X_D2, y_D2, random_state = 0)

fig, subaxes = plt.subplots(1, 1, figsize=(6, 6))

clf = GradientBoostingClassifier().fit(X_train, y_train)

title = 'Classificador Gradiente Aumentado'
plot_class_regions_for_classifier_subplot(clf, X_train, y_train, X_test,
                                          y_test, title, subaxes)

plt.show()
```

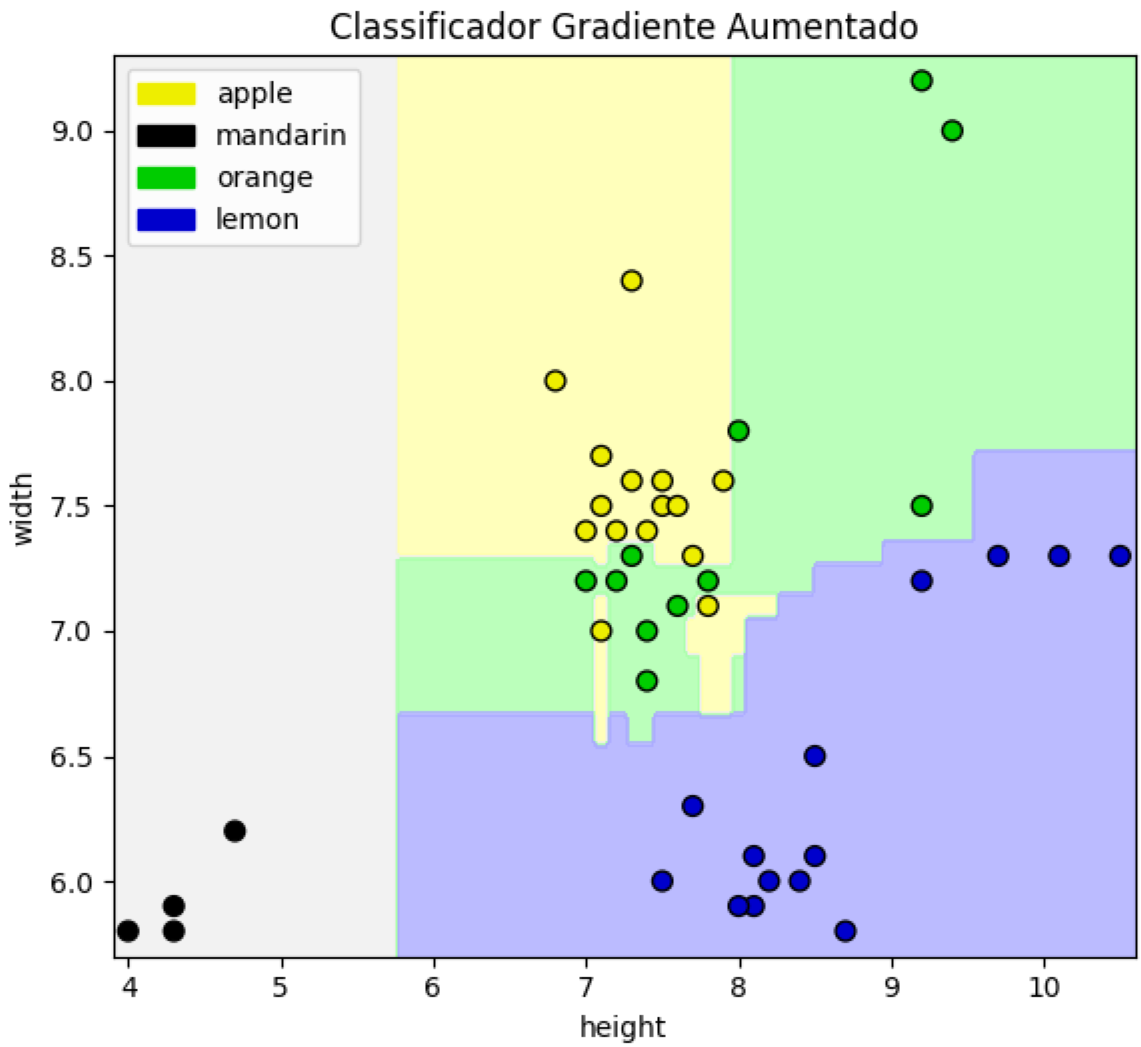


11 - Árvores com gradiente aumentado no dataset de frutas

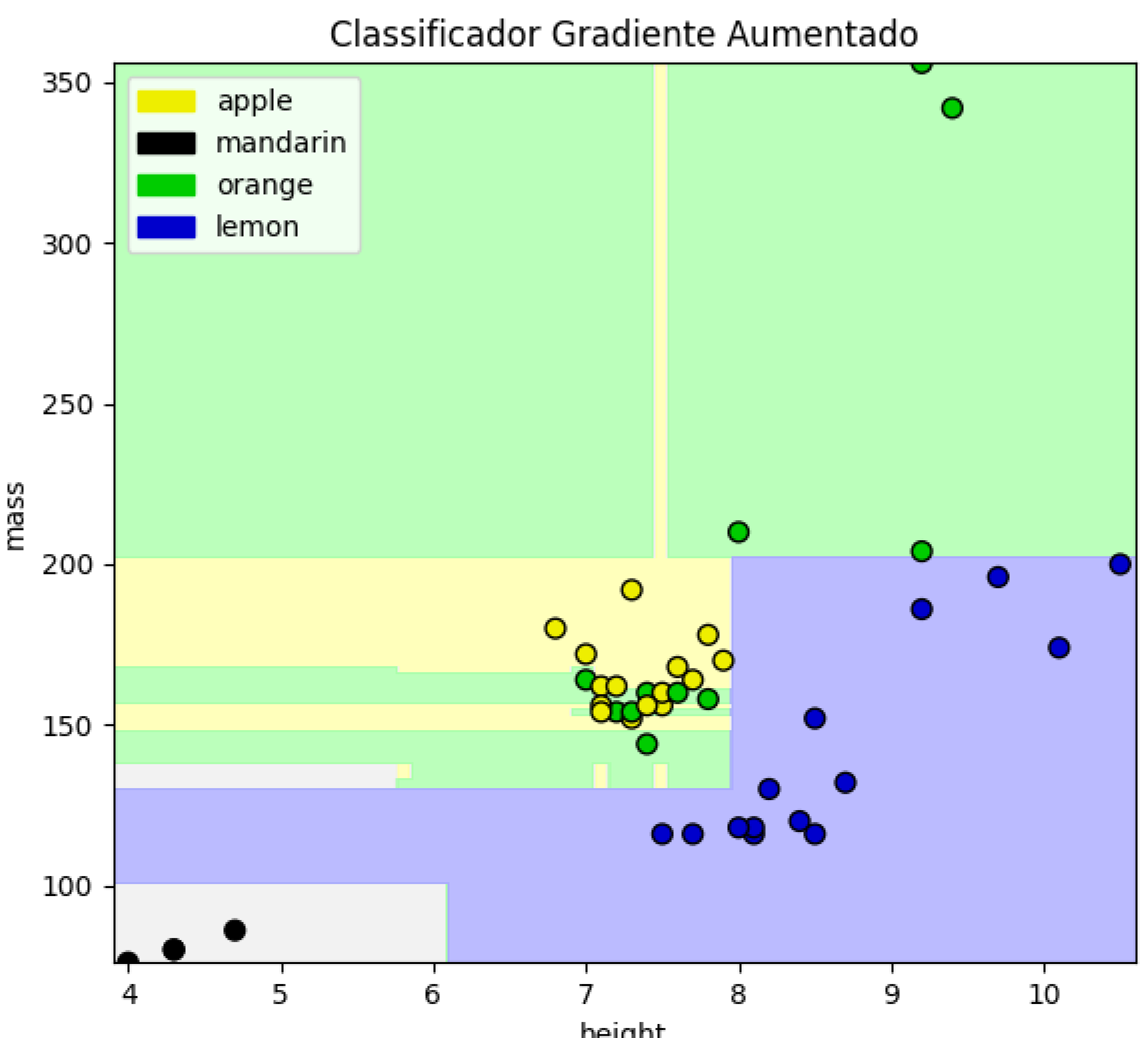
In [35]:

```python
X_train, X_test, y_train, y_test = train_test_split(X_fruits.to_numpy(), y_fruits.to_numpy
```

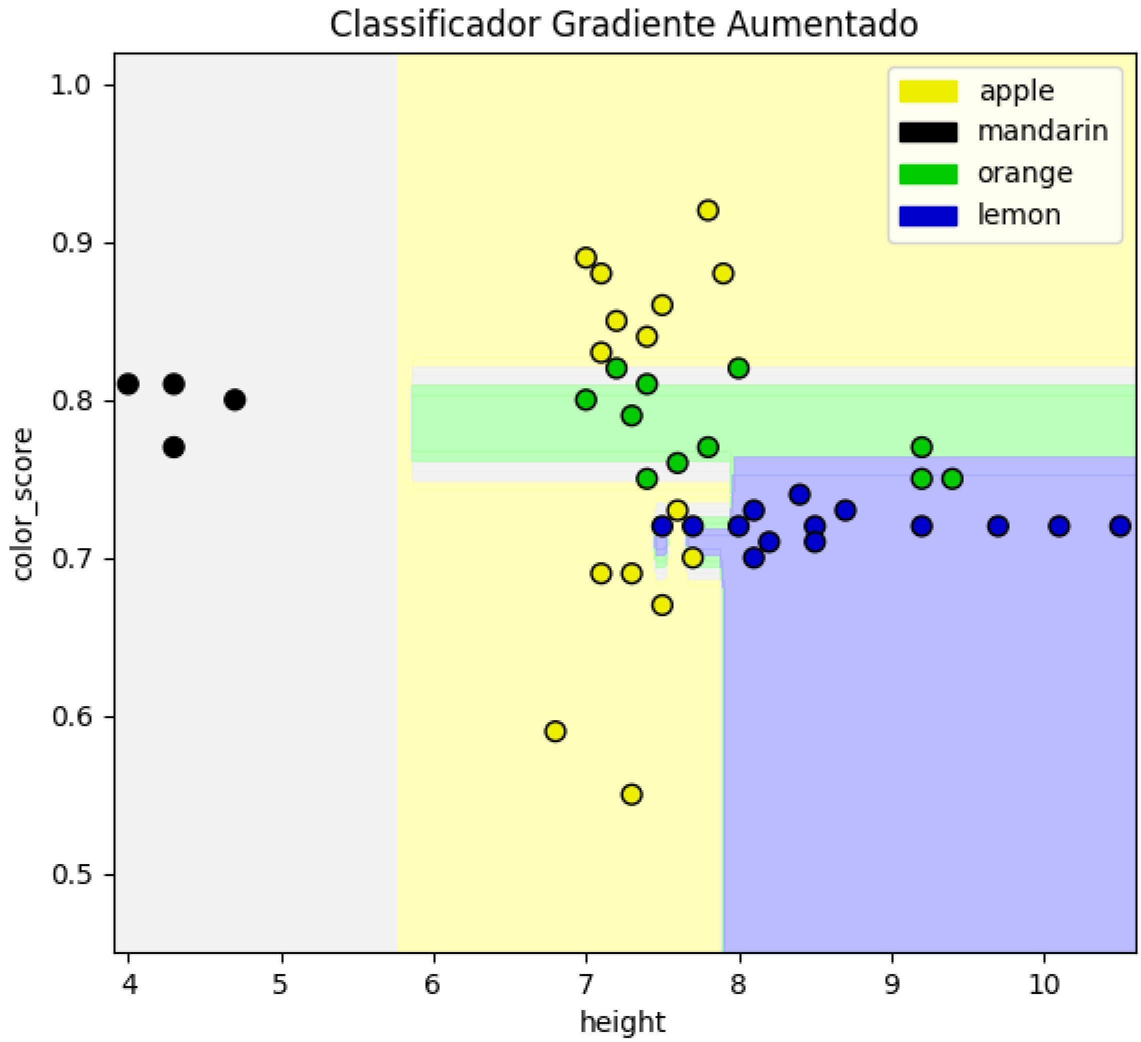
```
fig, subaxes = plt.subplots(6, 1, figsize=(6, 32))

clf = GradientBoostingClassifier?

pair_list = [[0,1], [0,2], [0,3], [1,2], [1,3], [2,3]]
for pair, axis in zip(pair_list, subaxes):
    X = X_train[:, pair]
    y = y_train

    clf = GradientBoostingClassifier().fit(X, y)
    plot_class_regions_for_classifier_subplot(clf, X, y, None,
                                              None, title, axis,
                                              target_names_fruits)

    axis.set_xlabel(feature_names_fruits[pair[0]])
    axis.set_ylabel(feature_names_fruits[pair[1]])

plt.tight_layout()
plt.show()

clf = GradientBoostingClassifier().fit(X_train, y_train)

print('Acurácia no treinamento: {:.2f}'.format(clf.score(X_train, y_train)))
print('Acurácia no teste: {:.2f}'.format(clf.score(X_test, y_test)))
```

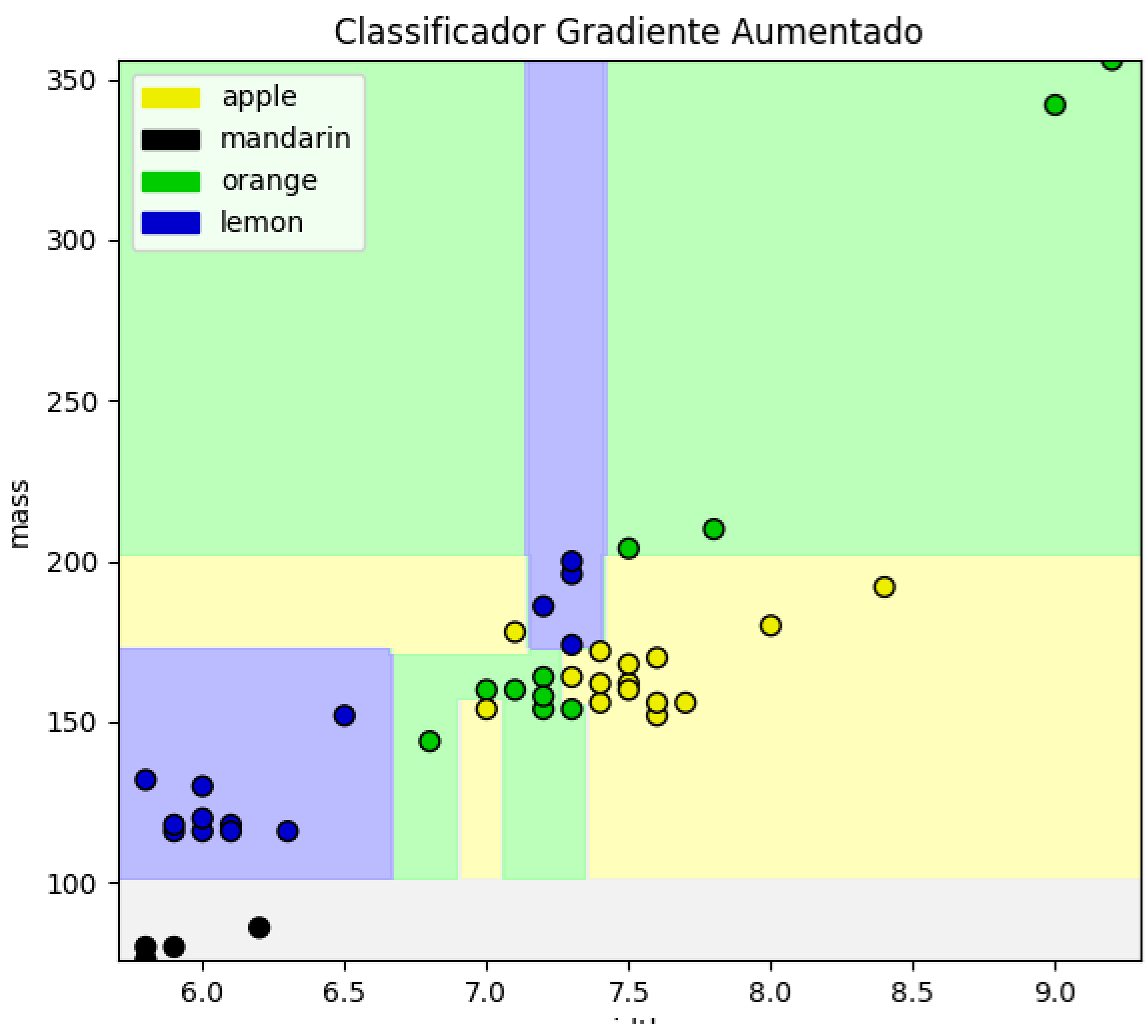


Classificador Gradiente Aumentado
apple
mandarin
orange
lemon
width
height
9.0
8.5
8.0
7.5
7.0
6.5
6.0
4
5
6
7
8
9
10

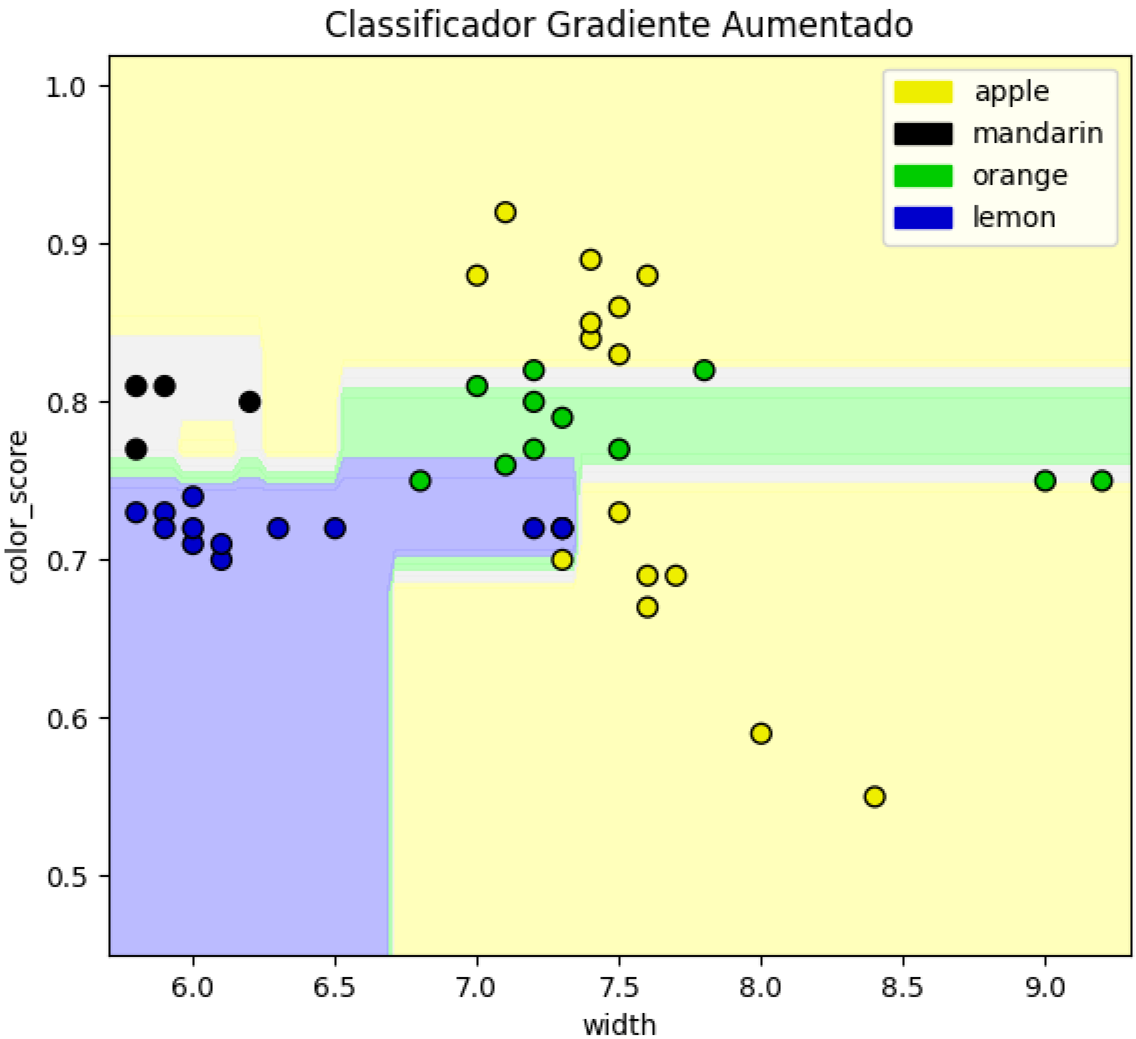


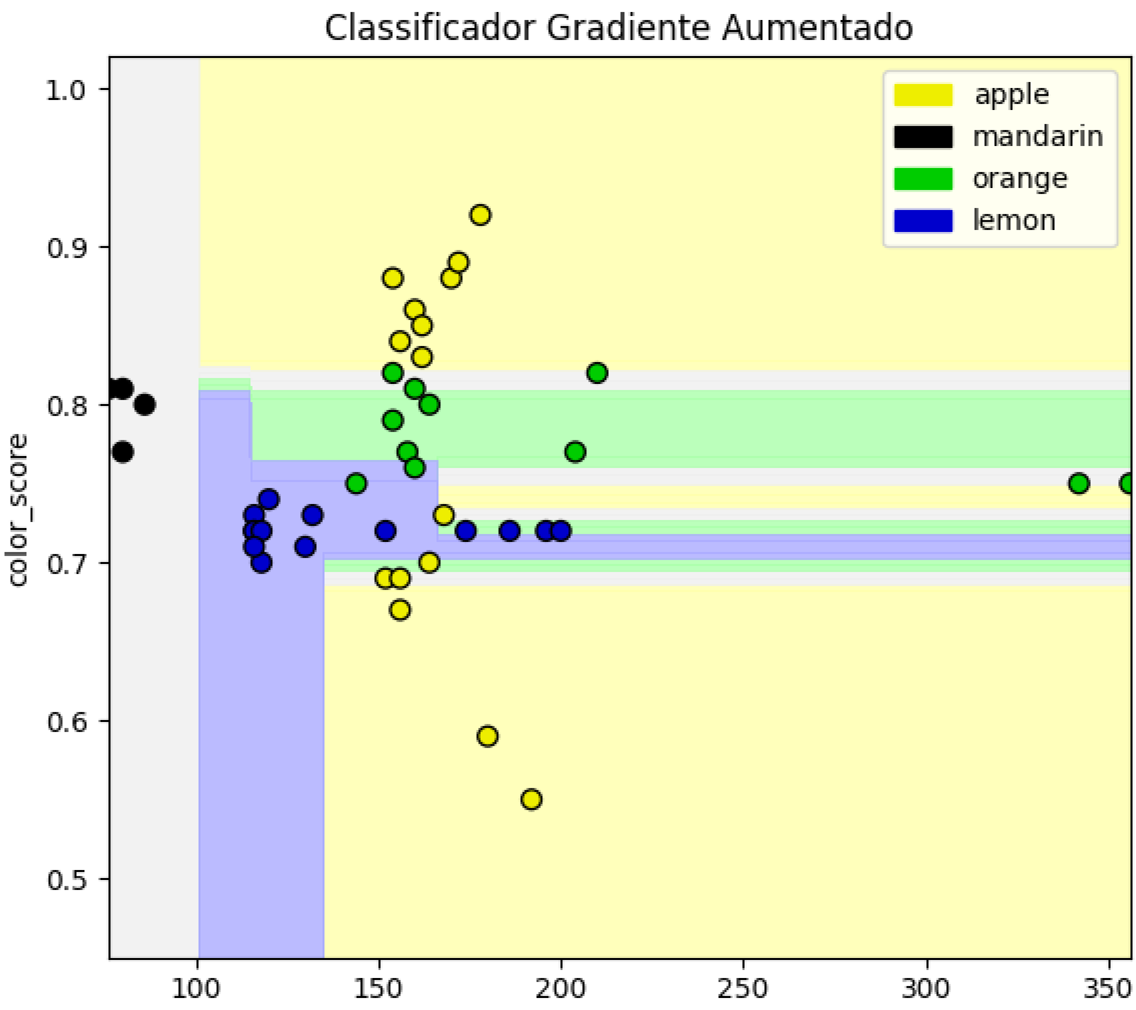
Classificador Gradiente Aumentado
apple
mandarin
orange
lemon
mass
height
350
300
250
200
150
100
4
5
6
7
8
9
10


Classificador Gradiente Aumentado
apple
mandarin
orange
lemon
color_score
1.0
0.9
0.8
0.7
0.6
0.5
4
5
6
7
8
9
10
height


Classificador Gradiente Aumentado
apple
mandarin
orange
lemon
mass
350
300
250
200
150
100
6.0
6.5
7.0
7.5
8.0
8.5
9.0

width


Classificador Gradiente Aumentado
apple
mandarin
orange
lemon
color_score
width
1.0
0.9
0.8
0.7
0.6
0.5
6.0
6.5
7.0
7.5
8.0
8.5
9.0


Classificador Gradiente Aumentado
apple
mandarin
orange
lemon
color_score
1.0
0.9
0.8
0.7
0.6
0.5
100
150
200
250
300
350

```
Acurácia no treinamento: 1.00
Acurácia no teste: 0.80
```

Modelos lineares para classificação multi-classe

12 - Função LinearSVC (Um contra todos)

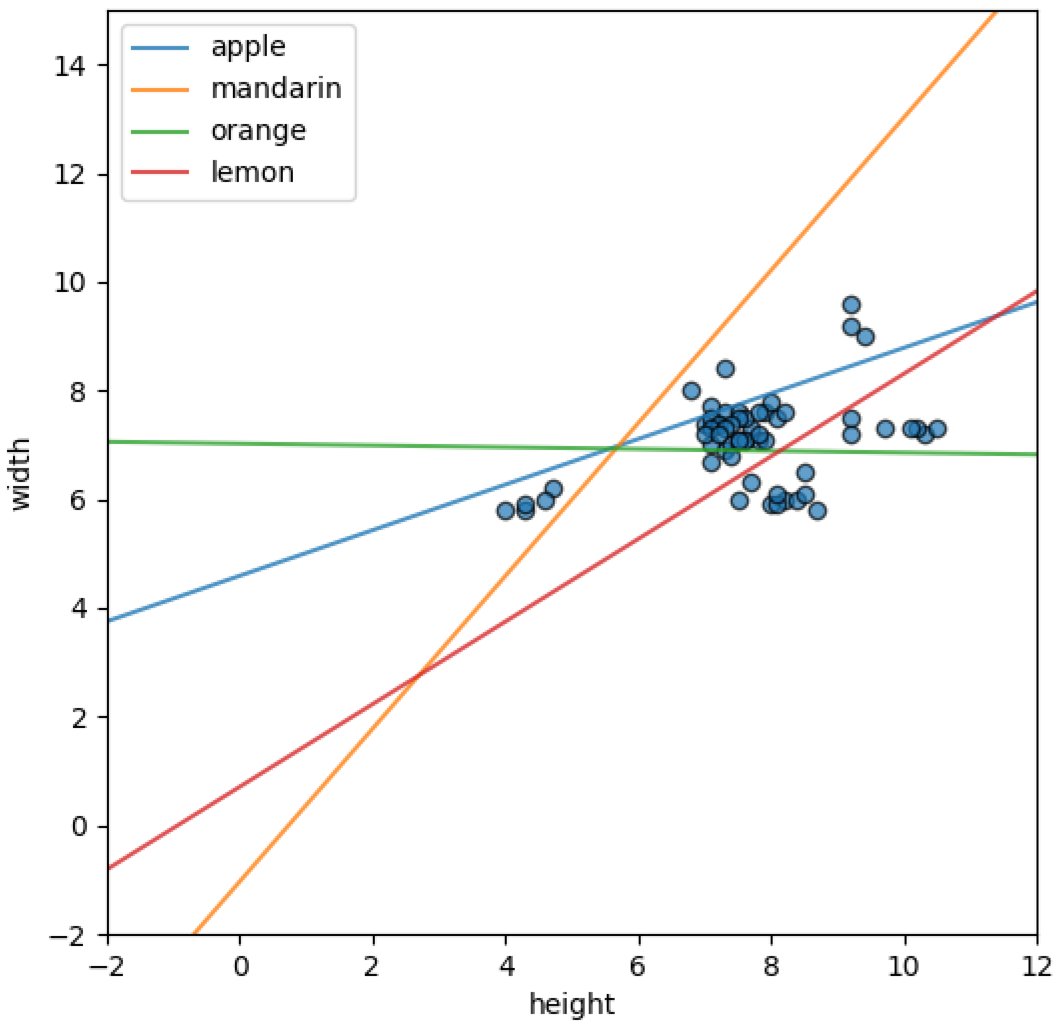
In [37]:
```
from sklearn.svm import LinearSVC

X_train, X_test, y_train, y_test = train_test_split(X_fruits_2d, y_fruits_2d, random_state

clf = LinearSVC(C=5, random_state = 67).fit(X_train, y_train)
print('Coeficientes:\n', clf.coef_)
print('Interceptos:\n', clf.intercept_)
```

```
Coeficientes:
 [[-0.30006303  0.71557482]
 [-1.62785586  1.15837035]
 [ 0.00721513  0.43311565]
 [ 1.2474674  -1.64209043]]
Interceptos:
 [-3.28519908  1.19823407 -3.04188368  1.16397746]
/Users/marinaramalhetedesouza/opt/anaconda3/envs/ml-impa/lib/python3.8/site-packages/sklea
rn/svm/_base.py:1206: ConvergenceWarning: Liblinear failed to converge, increase the numbe
r of iterations.
  warnings.warn(
```

!! -> coeficiente de regressão = declive da linha de regressão, pesos, estimativas de parâmetro -> intercepto = valor previsto quando x=0

13 - Plot dos resultados multi-classe

In [38]:
```
plt.figure(figsize=(6,6))
colors = ['r', 'g', 'b', 'y']
cmap_fruits = ListedColormap(['#FF0000', '#00FF00', '#0000FF','#FFFF00'])

plt.scatter(X_fruits_2d[['height']], X_fruits_2d[['width']],
           cmap=cmap_fruits, edgecolor = 'black', alpha=.7)

# falta c=y_fruits_2d
x_0_range = np.linspace(-10, 15)

for w, b, color in zip(clf.coef_, clf.intercept_, ['r', 'g', 'b', 'y']):
    plt.plot(x_0_range, -(x_0_range * w[0] + b) / w[1], alpha=.8)

plt.legend(target_names_fruits)
plt.xlabel('height')
plt.ylabel('width')
plt.xlim(-2, 12)
plt.ylim(-2, 15)
plt.show()
```



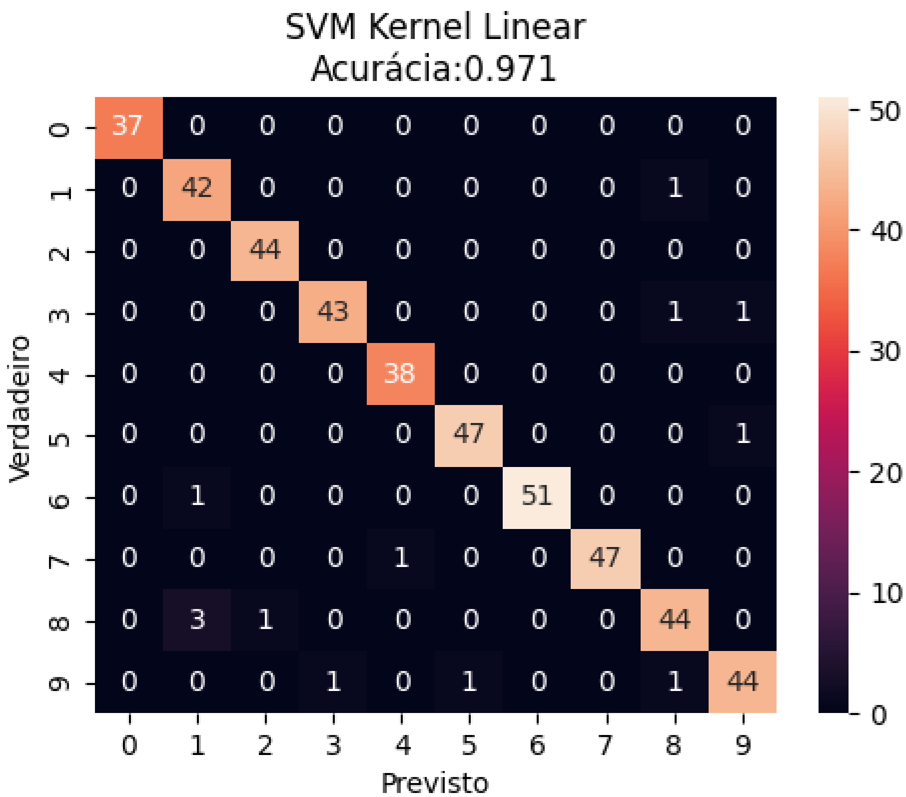
Avaliação para classificação multi-classe

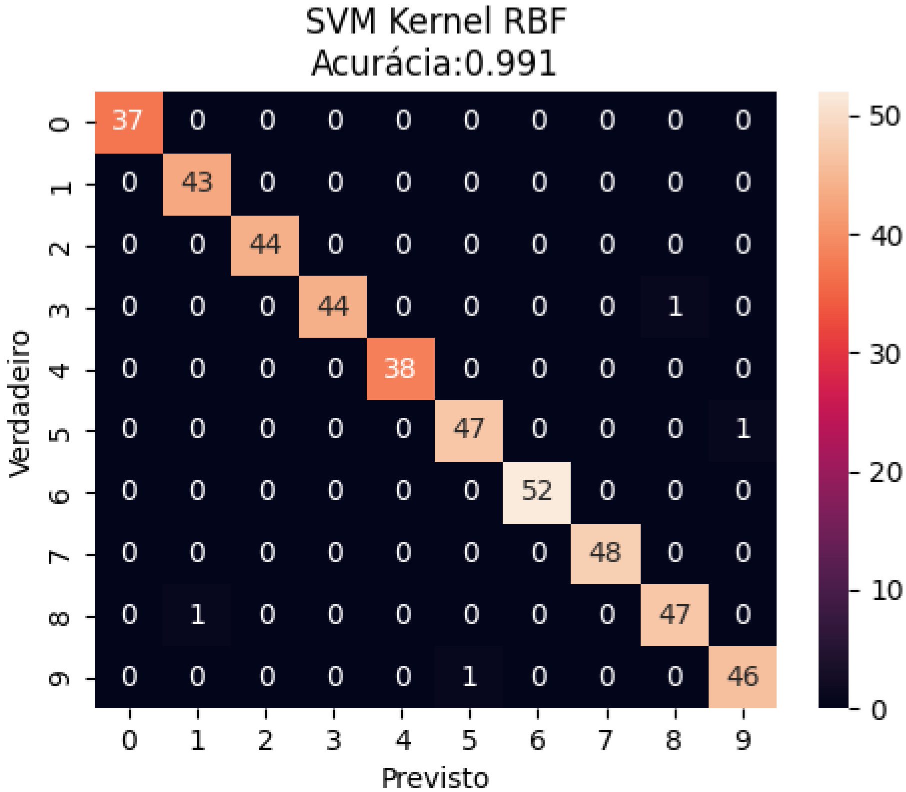
14 - Matriz de confusão multi-classe

In [39]:

```
from sklearn.metrics import confusion_matrix
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score

dataset = load_digits()
X, y = dataset.data, dataset.target
X_train_mc, X_test_mc, y_train_mc, y_test_mc = train_test_split(X, y, random_state=0)

##
svm = SVC(kernel = 'linear').fit(X_train_mc, y_train_mc)
svm_predicted_mc = svm.predict(X_test_mc)

confusion_mc = confusion_matrix(y_test_mc, svm_predicted_mc)
df_cm = pd.DataFrame(confusion_mc,
                     index = [i for i in range(0,10)], columns = [i for i in range(0,10)])

plt.figure(figsize=(5.5,4))
sns.heatmap(df_cm, annot=True)
plt.title('SVM Kernel Linear\nAcurácia:{0:.3f}'.format(accuracy_score(y_test_mc, svm_predi
plt.ylabel('Verdadeiro')
plt.xlabel('Previsto')
```

```
##
svm = SVC(kernel = 'rbf').fit(X_train_mc, y_train_mc)
svm_predicted_mc = svm.predict(X_test_mc)

confusion_mc = confusion_matrix(y_test_mc, svm_predicted_mc)
df_cm = pd.DataFrame(confusion_mc, index = [i for i in range(0,10)],
                     columns = [i for i in range(0,10)])

plt.figure(figsize = (5.5,4))
sns.heatmap(df_cm, annot=True)
plt.title('SVM Kernel RBF\nAcurácia:{0:.3f}'.format(accuracy_score(y_test_mc, svm_predicte
plt.ylabel('Verdadeiro')
plt.xlabel('Previsto');
```





15 - Reporte de classificação multi-classe

In [40]:

```
from sklearn.metrics import classification_report

print(classification_report(y_test_mc, svm_predicted_mc))
```

```
              precision    recall  f1-score   support

           0       1.00      1.00      1.00        37
           1       0.98      1.00      0.99        43
           2       1.00      1.00      1.00        44
           3       1.00      0.98      0.99        45
           4       1.00      1.00      1.00        38
           5       0.98      0.98      0.98        48
           6       1.00      1.00      1.00        52
           7       1.00      1.00      1.00        48
           8       0.98      0.98      0.98        48
           9       0.98      0.98      0.98        47

    accuracy                           0.99       450
   macro avg       0.99      0.99      0.99       450
weighted avg       0.99      0.99      0.99       450
```

16 - Micro vs. Macro metrics

In [41]:

```
print('Precisão Micro-média = {:.2f} (trata as instâncias igualmente)'
      .format(precision_score(y_test_mc, svm_predicted_mc, average = 'micro')))
print('Precisão Macro-média = {:.2f} (trata as classes igualmente)\n'
      .format(precision_score(y_test_mc, svm_predicted_mc, average = 'macro')))


print('Micro-média f1 = {:.2f} (trata as instâncias igualmente)'
      .format(f1_score(y_test_mc, svm_predicted_mc, average = 'micro')))
print('Macro-média f1 = {:.2f} (trata as classes igualmente)'
      .format(f1_score(y_test_mc, svm_predicted_mc, average = 'macro')))
```

```
Precisão Micro-média = 0.99 (trata as instâncias igualmente)
```

```
Precisão Macro-média = 0.99 (trata as classes igualmente)

Micro-média f1 = 0.99 (trata as instâncias igualmente)
Macro-média f1 = 0.99 (trata as classes igualmente)
```

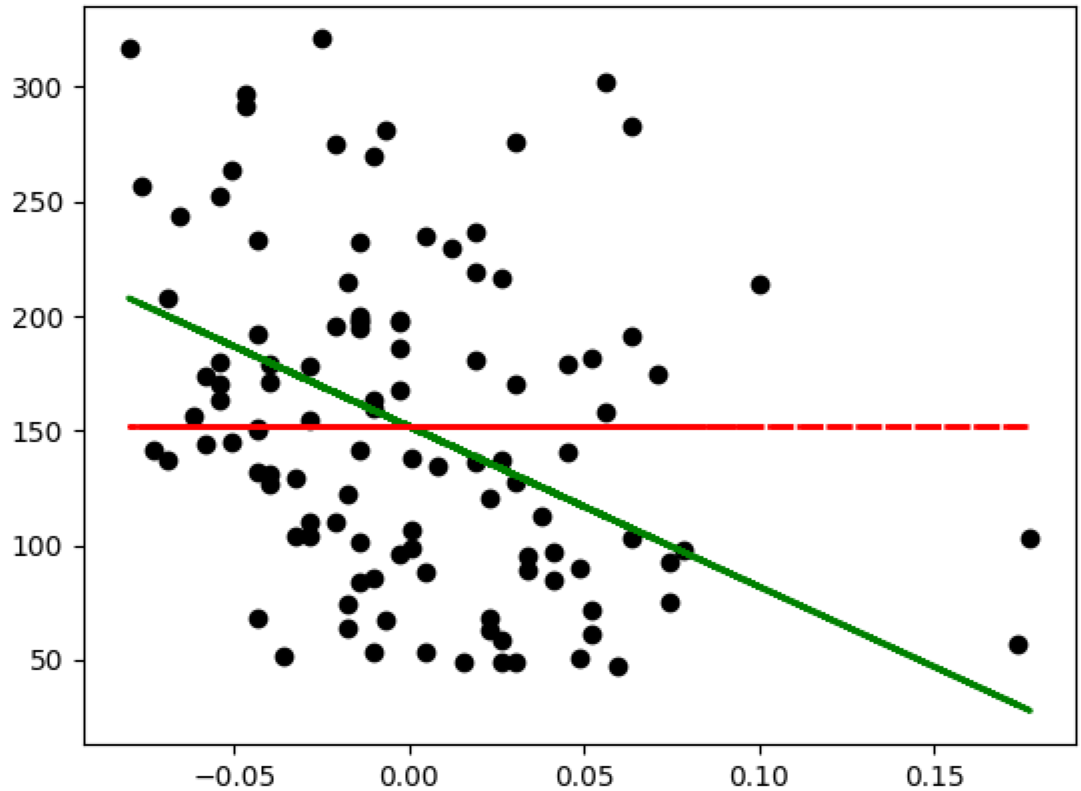
Métrica para Regressão

17 - Exemplo com a função LinearRegression()

In [42]:

```
%matplotlib notebook
import matplotlib.pyplot as plt
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn import datasets
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error, r2_score
from sklearn.dummy import DummyRegressor

diabetes = datasets.load_diabetes()

X = diabetes.data[:, None, 6]
y = diabetes.target

X_train, X_test, y_train, y_test = train_test_split(X, y, random_state=0)

lm = LinearRegression().fit(X_train, y_train)
lm_dummy_mean = DummyRegressor(strategy = 'mean').fit(X_train, y_train)

y_predict = lm.predict(X_test)
y_predict_dummy_mean = lm_dummy_mean.predict(X_test)

print('Coeficientes: ', lm.coef_)
print("Erro quadrado médio (dummy): {:.2f}".format(mean_squared_error(y_test,
                                                                     y_predict_dummy_mean)
print("Erro quadrado médio (linear model): {:.2f}".format(mean_squared_error(y_test, y_pre
print("Escore r2 (dummy): {:.2f}".format(r2_score(y_test, y_predict_dummy_mean)))
print("Escore r2 (linear model): {:.2f}".format(r2_score(y_test, y_predict)))

# Plot outputs
plt.scatter(X_test, y_test,  color='black')
plt.plot(X_test, y_predict, color='green', linewidth=2)
plt.plot(X_test, y_predict_dummy_mean, color='red', linestyle = 'dashed',
         linewidth=2, label = 'dummy')

plt.show()
```

```
Coeficientes:  [-698.80206267]
Erro quadrado médio (dummy): 4965.13
Erro quadrado médio (linear model): 4646.74
Escore r2 (dummy): -0.00
Escore r2 (linear model): 0.06
```



In [ ]: