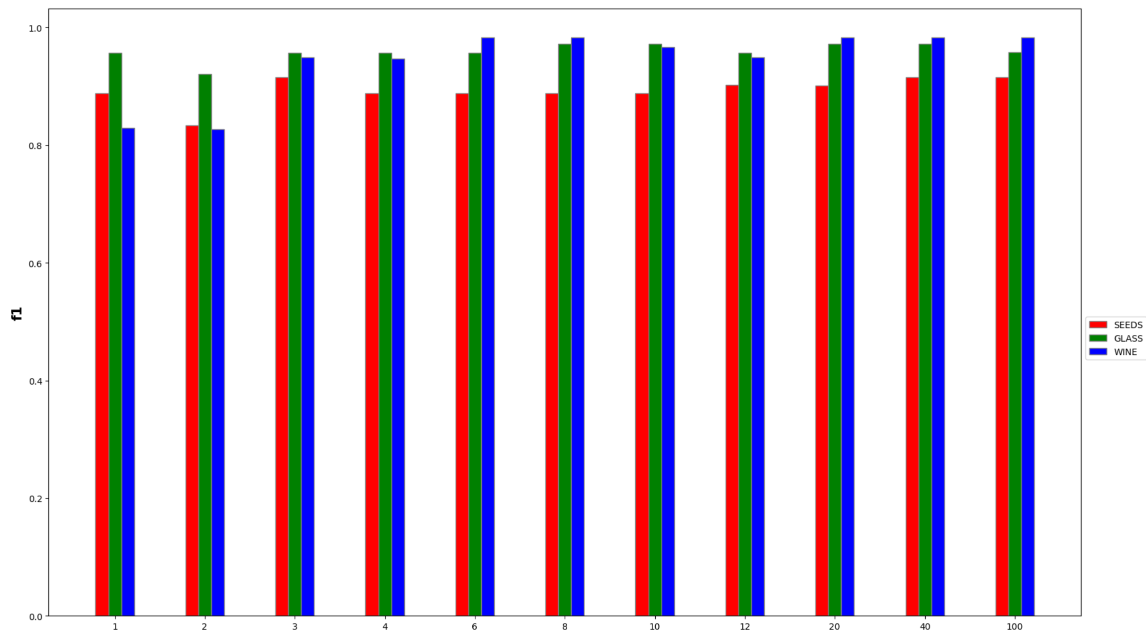
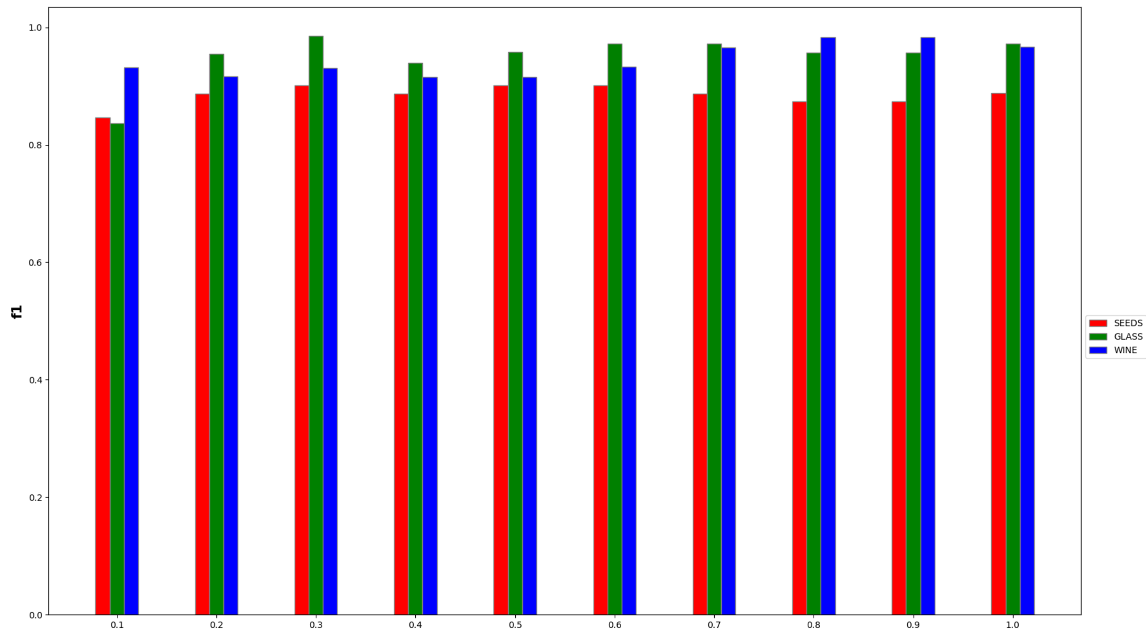
Wnioski

Bagging

Badając wpływ liczby klasyfikatorów. Ze wzrostem tego parametru wzrasta f1-score, jednak optymalna wartość jest w środku zakresu badanych wartości. Zbiór GLASS się nie zmienia, bo ten zbiór jest specyficzny.



Max smaples też ogólnie polepsza wyniki, ale dla co datasetu możemy wyznaczyć optymalną wartość, jednak możliwie to spowodowane wadanie wartości podanej jako %.

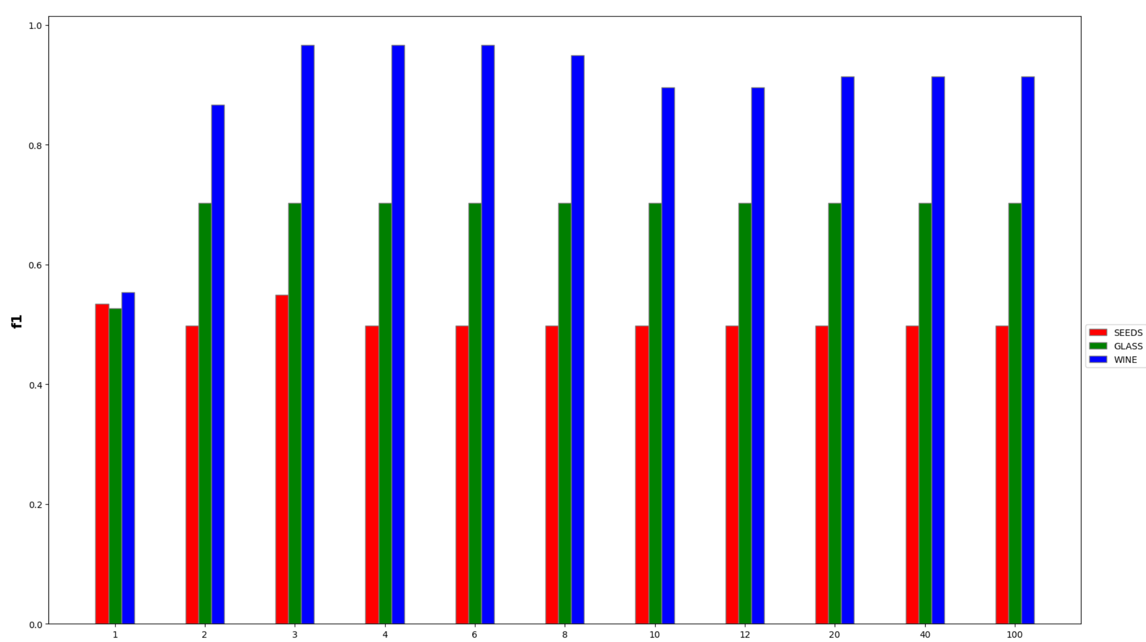


Liczba atrybutów daje gorsze wyniki dla małych wartości, ale optymalne wartości są w środku zakresu.

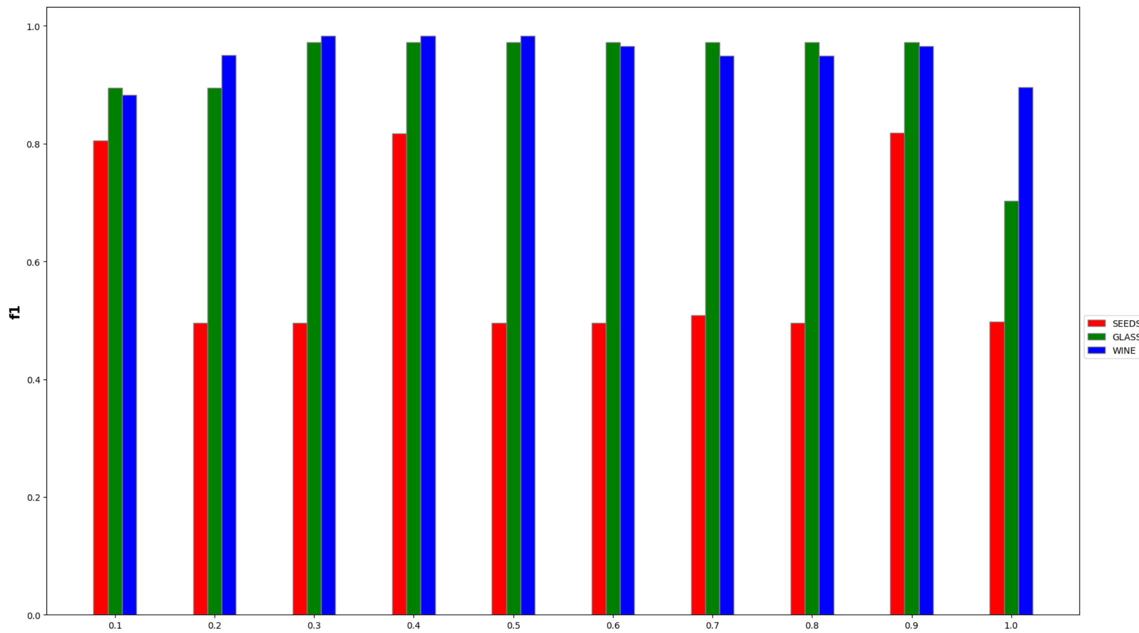
Zmiany zpowodowane różnymy wartościami bootstrap nie są znaczące.

AdaBoost

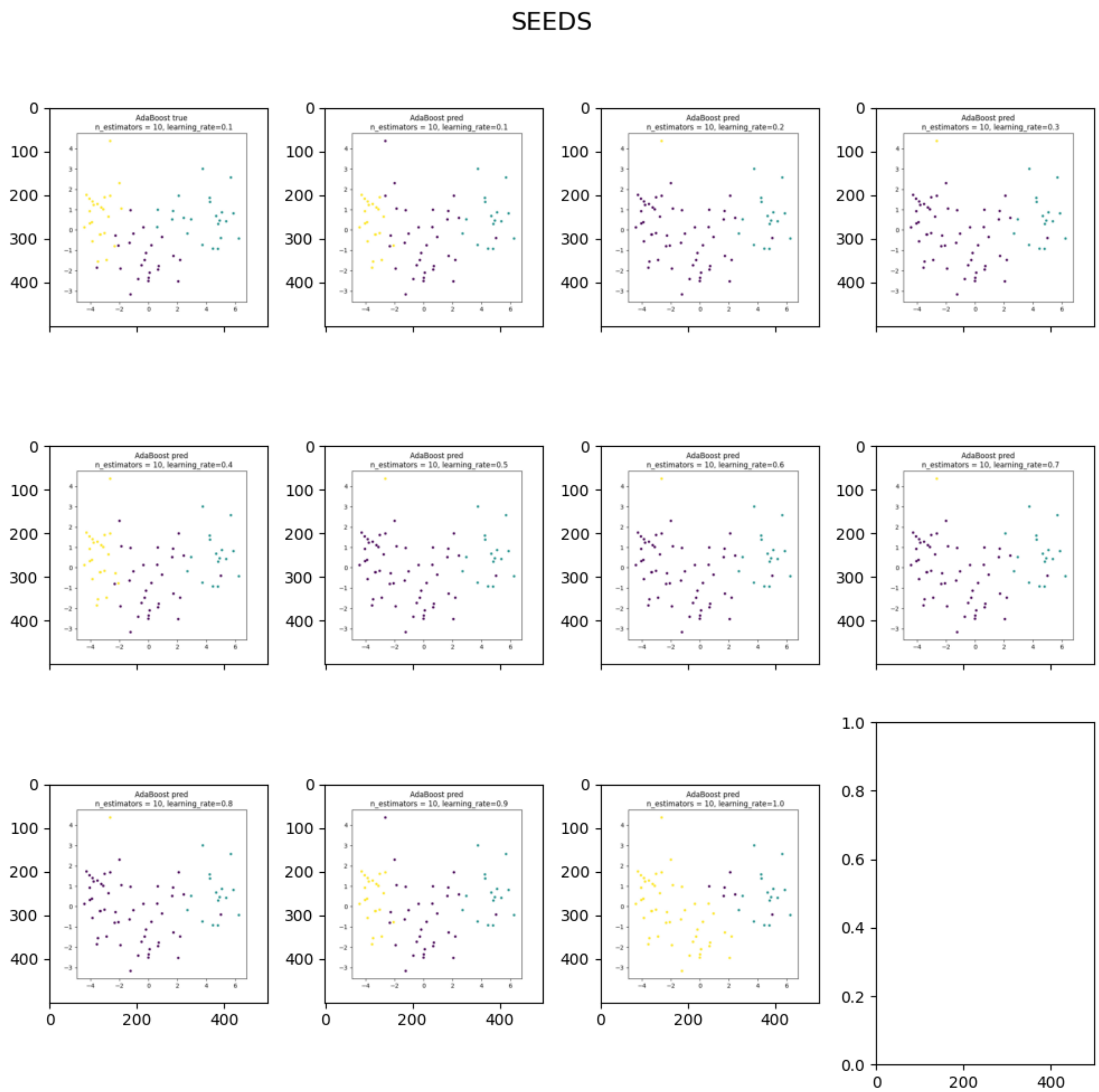
W przypadku liczby klasyfikatorów tutaj też możemy zobaczyć, że wartości w środku, 2,4,6, dają same optymalne wyniki dla WINE. GLASS robi swoje rzeczy, a SEEDS się nie udało polepszyć.



Badając współczynnik uczeniadla zbiorów GLASS i WINE nic dziwnego się nie zdażyło, niektóre wartości lepsze, niektóre gorsze, jednak SEEDS zachowywał się dziwno



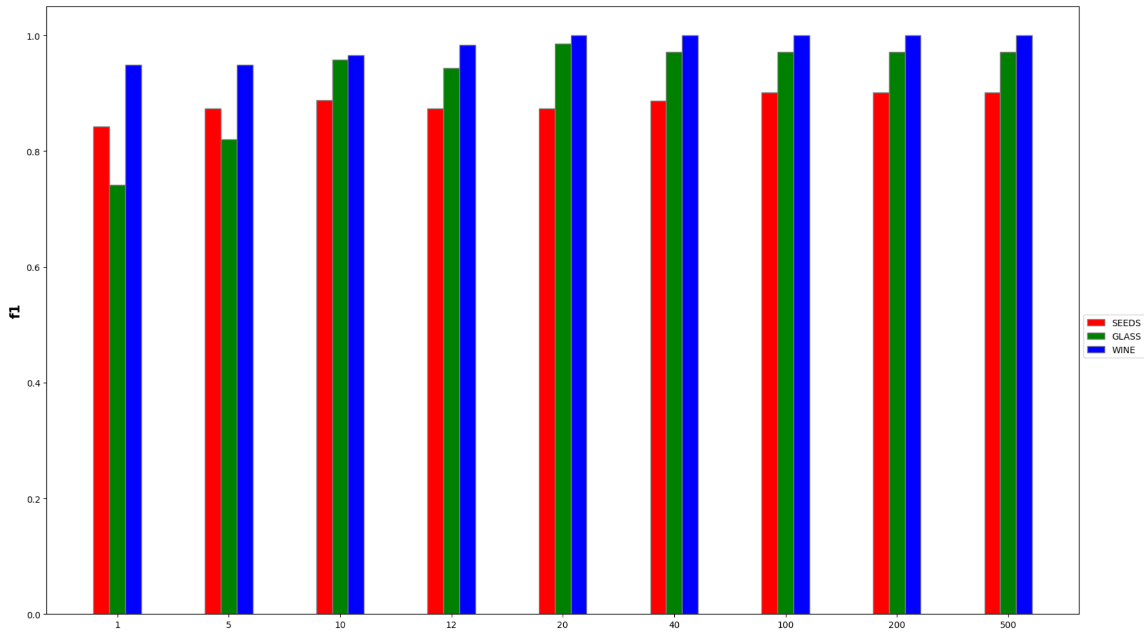
Aby zrozumieć, co się dizieje, popatrzyłem na wizualizacje



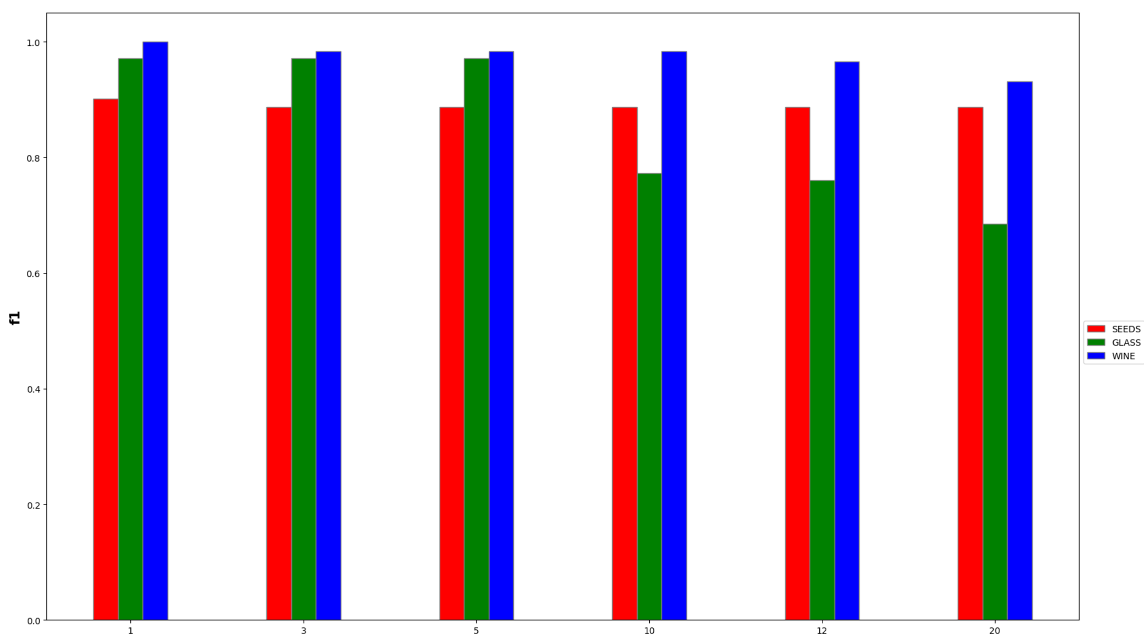
Widać, że dla wartości oprócz 0.1, 0.4 i 0.9 adaboost pracuje bardzo średnio i nie ma nawet wszystkich trzech klas.

Random forest

Nic ciekawego z liczbą drzew, można znaleźć optymalną wartość dla co zbioru



Duża wartość liczby samplów pogorszyła rezultat dla GLASS, ale pozostałe zbiory mało odczuły zmiany.



Grając z liczbą cech można polepszyć wynik, ale rezultat jest +- taki sam dla wszystkich zbiorów

Głębokość też nie dała duże zmiany

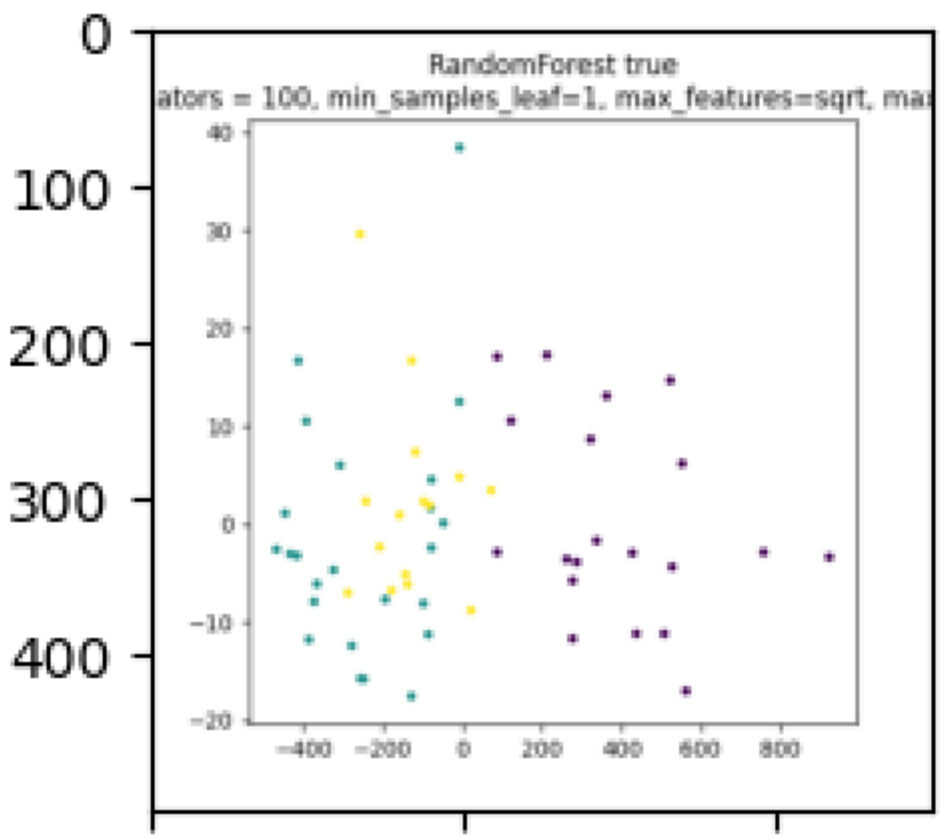
Porównanie z klasyfikatorem bazowym

Sprawdzimy wartości f1 dla parametrów domyślnych tech klasyfikatorów

	f1 KNN	f1 bagging	f1 boost	f1 forest
IRIS	0.980000	1.000000	0.878487	0.980000
SEEDS	0.885714	0.887773	0.498168	0.901039
GLASS	0.957746	0.971702	0.702701	0.971702
WINE	0.677966	0.966270	0.895931	1.000000

IRIS, SEEDS i GLASS powodują sobie podobnie: wszystkie metody ensemble oprocz boosting dają lepsze wyniki.

Ale najciekawsze są wyniki dla WINE, gdzie ensemble dają znacznie lepsze wyniki. Zobaczmy jak wygląda ten dataset.



I odrazu widać dlaczego, bo dane tutaj są zmieszane (dla 2 klas). A metody ensemble, ogolna idea ktorych to wykorzystanie kilka klasyfikatorow aby jedne klasyfikatory negowały błędy innych klasyfikatorow, jest w stanie złapać takie struktury. w odrożnieniu od klasyfikatorow bazowych

Część techniczna

In [ ]:
```
import matplotlib.pyplot as plt
import matplotlib as matplotlib

# unused but required import for doing 3d projections with matplotlib < 3.2
import mpl_toolkits.mplot3d  # noqa: F401
import numpy
import pandas as pd
from sklearn import datasets
from sklearn.decomposition import PCA
from sklearn.model_selection import train_test_split
from scipy.io import arff
```

In [ ]:
```
iris = datasets.load_iris()
df_iris = pd.DataFrame(iris.data, columns=['sepal length', 'sepal width', 'pepal le
df_iris = pd.concat([df_iris, pd.DataFrame(iris.target, columns=['name'])], axis=1
```

In [ ]:
```
import requests

data_seeds_raw = requests.get('https://archive.ics.uci.edu/ml/machine-learning-data
data_seeds = ''
for data in (data_seeds_raw.iter_content()):
    data_seeds = data_seeds + data.decode("utf-8")

data_seeds_split = data_seeds.split('\n')
data_seeds = []

for x in data_seeds_split:
    if x != '':
        data_seeds.append([float(xx) for xx in x.split('\t') if xx != ''])

data_seeds = numpy.array(data_seeds)

df_seeds = pd.DataFrame(data_seeds)

df_seeds = df_seeds.astype({7: int})
df_seeds = df_seeds.rename(columns = {7: 'name'})
df_seeds.columns = df_seeds.columns.astype(str)
```

In [ ]:
```
import requests

data_glass_raw = requests.get('https://archive.ics.uci.edu/ml/machine-learning-data

data_glass = ''
for data in (data_glass_raw.iter_content()):
    data_glass = data_glass + data.decode("utf-8")
data_glass_split = data_glass.split('\n')
data_glass = []
for x in data_glass_split:
    if x != '':
        data_glass.append([float(xx) for xx in x.split(',')])


data_glass = numpy.array(data_glass)

df_glass = pd.DataFrame(data_glass)

df_glass = df_glass.astype({10: int})
df_glass = df_glass.rename(columns = {10: 'name'})
df_glass.columns = df_glass.columns.astype(str)
```

In [ ]:
```
dict_attr_wine = {
    0 : 'Alcohol',
    1 : 'Malic acid',
    2 : 'Ash',
    3 : 'Alcalinity of ash' ,
    4 : 'Magnesium',
    5 : 'Total phenols',
    6 : 'Flavanoids',
    7 : 'Nonflavanoid phenols',
    8 : 'Proanthocyanins',
    9 : 'Color intensity',
    10: 'Hue',
    11: 'OD280/OD315 of diluted wines',
    12: 'Proline'
}

wine = datasets.load_wine()
df_wine = pd.DataFrame(wine.data, columns=dict_attr_wine.values())
df_wine = pd.concat([df_wine, pd.DataFrame(wine.target, columns=['name'])], axis=1
```

In [ ]:
```
import math
import numpy as np
def plotStatistics(df, metrics, col_names, dataset_names, colours):
    size_height = math.ceil(len(metrics)/2)
    size_width = math.ceil((len(metrics))/size_height)
    fig, axes = plt.subplots(size_height, size_width, sharex=True, sharey=False, fi

    for i in range(len(metrics)):
        col_id = i % size_width
        row_id = i // size_width


        y = [[exp_data[metrics[i]] for exp_data in ds_data ] for ds_data in df]

        barWidth =1 / (len(y) + 4)

        brs = []
        brs.append(np.arange(len(y[0])))

        for j in range(1, len(y)):
            brs.append([x + barWidth for x in brs[j-1]])

        for j in range(len(y)):
            if len(metrics) == 1:
                axes.bar(brs[j], y[j], color = colours[j], width = barWidth,
                    edgecolor ='grey', label =dataset_names[j])
            elif size_height > 1:
                axes[row_id][col_id].bar(brs[j], y[j], color = colours[j], width =
                    edgecolor ='grey', label =dataset_names[j])
            else:
                axes[col_id].bar(brs[j], y[j], color = colours[j], width = barWidth
                    edgecolor ='grey', label =dataset_names[j])

        # axes[row_id][col_id].set_xlabel('Value', fontweight ='bold', fontsize = 1
        if len(metrics) == 1:
            axes.set_ylabel(metrics[i], fontweight ='bold', fontsize = 15)
            axes.set_xticks([r + barWidth for r in range(len(y[0]))],
                    col_names)

            axes.legend(bbox_to_anchor=(1, 0.5), fancybox=True)
        elif size_height > 1:
            axes[row_id][col_id].set_ylabel(metrics[i], fontweight ='bold', fontsiz
            axes[row_id][col_id].set_xticks([r + barWidth for r in range(len(y[0]))
                    col_names)

            axes[row_id][col_id].legend(bbox_to_anchor=(1, 0.5), fancybox=True)
        else:
            axes[col_id].set_ylabel(metrics[i], fontweight ='bold', fontsize = 15)
            axes[col_id].set_xticks([r + barWidth for r in range(len(y[0]))],
                    col_names)

            axes[col_id].legend(bbox_to_anchor=(1, 0.5), fancybox=True)


    plt.tight_layout()
```

```python
# plotStatistics(results_list_criterion, ['silhouette_score', 'davies_bouldin_score
```

In [ ]:
```python
from io import BytesIO

def combineFigsInOnePlot(dict_list, plot_name = ''):
    size_width = min(4, len(dict_list) + 1)
    size_height = math.ceil((len(dict_list) + 1)/size_width)
    fig, axes = plt.subplots( size_height, size_width, sharex=True, sharey=False, f

    buffer_tru = BytesIO()
    dict_list[0]['true_fig'].savefig(buffer_tru, format='png')
    buffer_tru.seek(0)
    image_true_data = plt.imread(buffer_tru)

    if size_height > 1:
        axes[0][0].imshow(image_true_data)
    else:
        axes[0].imshow(image_true_data)

    for i in range(len(dict_list)):
        col_id = (i + 1) % size_width
        row_id = (i + 1) // size_width

        buffer = BytesIO()
        dict_list[i]['pred_fig'].savefig(buffer, format='png')
        buffer.seek(0)
        image_data = plt.imread(buffer)

        if size_height > 1:
            axes[row_id][col_id].imshow(image_data)
        else:
            axes[col_id].imshow(image_data)

    fig.suptitle(plot_name, fontsize=16)
    plt.tight_layout()
```

Klasyfikator bazowy

In [ ]:
```python
from sklearn.model_selection import StratifiedKFold
from sklearn.model_selection import KFold
from sklearn.neighbors import KNeighborsClassifier
from sklearn.model_selection import train_test_split
from sklearn.model_selection import cross_val_score
import sklearn.metrics as skmet

def RunKNN (df, n_neighbors = 5, weights = 'uniform', metric = 'minkowski', cv = 3,
    neigh = KNeighborsClassifier(n_neighbors = n_neighbors, metric = metric, weight

    df_train, df_test = train_test_split( df, test_size=0.33, random_state=42)

    neigh.fit(df_train.iloc[:, :-1], df_train.iloc[:, -1])

    y_true = df_test.iloc[:, -1].tolist()
    y_pred = neigh.predict(df_test.iloc[:, :-1])

    strat_k_fold = None
    if isStratified:
        strat_k_fold = StratifiedKFold(n_splits=cv, shuffle=True, random_state=42)
    else:
        strat_k_fold = KFold(n_splits=cv, shuffle=True, random_state=42)

    cross_val = cross_val_score(neigh, df.iloc[:, :-1], df.iloc[:, -1], cv=strat_k_
    cross_val = cross_val.mean()

    if print_metrics:
        print(skmet.classification_report(y_true, y_pred))
        print('Cross val: ', cross_val)

    return {'f1':skmet.f1_score(y_true, y_pred, average='micro'), 'cross-val': cros

RunKNN(df_iris, cv = 3)
```

```
              precision    recall  f1-score   support

           0       1.00      1.00      1.00        19
           1       0.94      1.00      0.97        15
           2       1.00      0.94      0.97        16

    accuracy                           0.98        50
   macro avg       0.98      0.98      0.98        50
weighted avg       0.98      0.98      0.98        50

Cross val:  0.9666666666666667
```

Out[ ]:
```
{'f1': 0.98, 'cross-val': 0.9666666666666667}
```

In [ ]:
```
score_metric = 'f1'
results_df = pd.DataFrame([
[RunKNN (df_iris, print_metrics = False)[score_metric], RunKNN (df_iris, print_metr
[RunKNN (df_seeds, print_metrics = False)[score_metric], RunKNN (df_seeds, print_me
[RunKNN (df_glass, print_metrics = False)[score_metric], RunKNN (df_glass, print_me
[RunKNN (df_wine, print_metrics = False)[score_metric], RunKNN (df_wine, print_metr
], index=['IRIS', 'SEEDS', 'GLASS', 'WINE'], columns = ['f1', 'cross_val'])

results_df
```

Out[ ]:

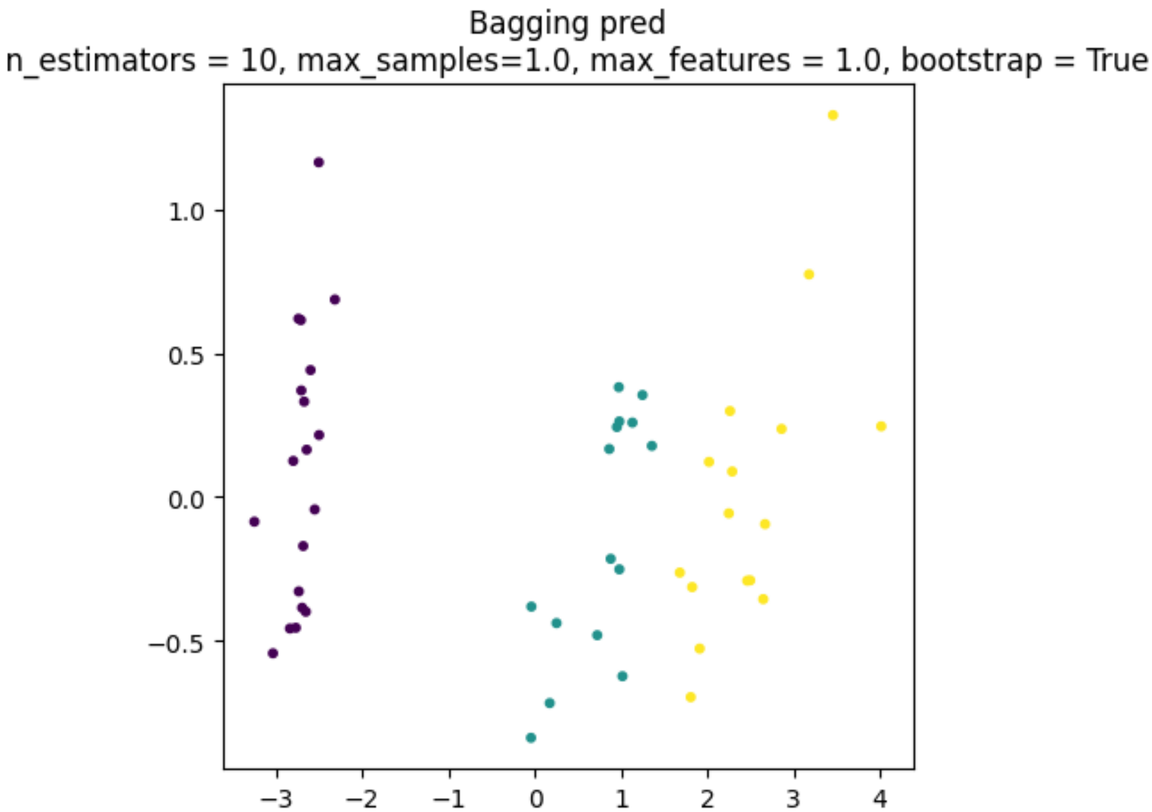
	f1	cross_val
IRIS	0.980000	0.966667
SEEDS	0.885714	0.904762
GLASS	0.957746	0.976721
WINE	0.677966	0.640207

Bagging

In [ ]:
```
from sklearn.metrics import f1_score
from sklearn.cluster import KMeans
from sklearn.pipeline import Pipeline
from sklearn.impute import SimpleImputer
from sklearn.preprocessing import StandardScaler
import numpy as np
from sklearn.ensemble import BaggingClassifier

def run_bagging(df, n_estimators = 10, max_samples = 1.0, max_features = 1.0, boots
    df_train, df_test = train_test_split( df, test_size=0.33, random_state=42)
    clf = BaggingClassifier(n_estimators = n_estimators, max_samples = max_samples,
    clf = Pipeline([('imputate', SimpleImputer( strategy='mean')),
                    ('standardization', StandardScaler()),
                    ('clf', clf),])

    clf.fit(df_train.iloc[:, :-1], df_train.iloc[:, -1])

    y_true = df_test.iloc[:, -1].tolist()
    y_pred = clf.predict(df_test.iloc[:, :-1])

    X_reduced = PCA(n_components=2).fit_transform(df_test)

    pred_fig = plt.figure(1, figsize=(5, 5))
    ax1 = pred_fig.add_subplot()
    ax1.scatter(X_reduced[:, 0], X_reduced[:, 1], s=10, c=y_pred)
    ax1.set_title(f"Bagging pred\n  n_estimators = {n_estimators}, max_samples={max
    plt.close()

    true_fig = plt.figure(2, figsize=(5, 5))
    ax2 = true_fig.add_subplot()
    ax2.scatter(X_reduced[:, 0], X_reduced[:, 1], s=10, c=y_true)
    ax2.set_title(f"Bagging true\n  n_estimators = {n_estimators}, max_samples={max
    plt.close()

    f1 = f1_score(y_true, y_pred, average='weighted')

    return {'f1':f1,
            'pred_fig': pred_fig, 'true_fig': true_fig,}

test_run = run_bagging(df_iris)
print(test_run['f1'])
test_run['pred_fig']
```

```
1.0
```

Out[ ]:

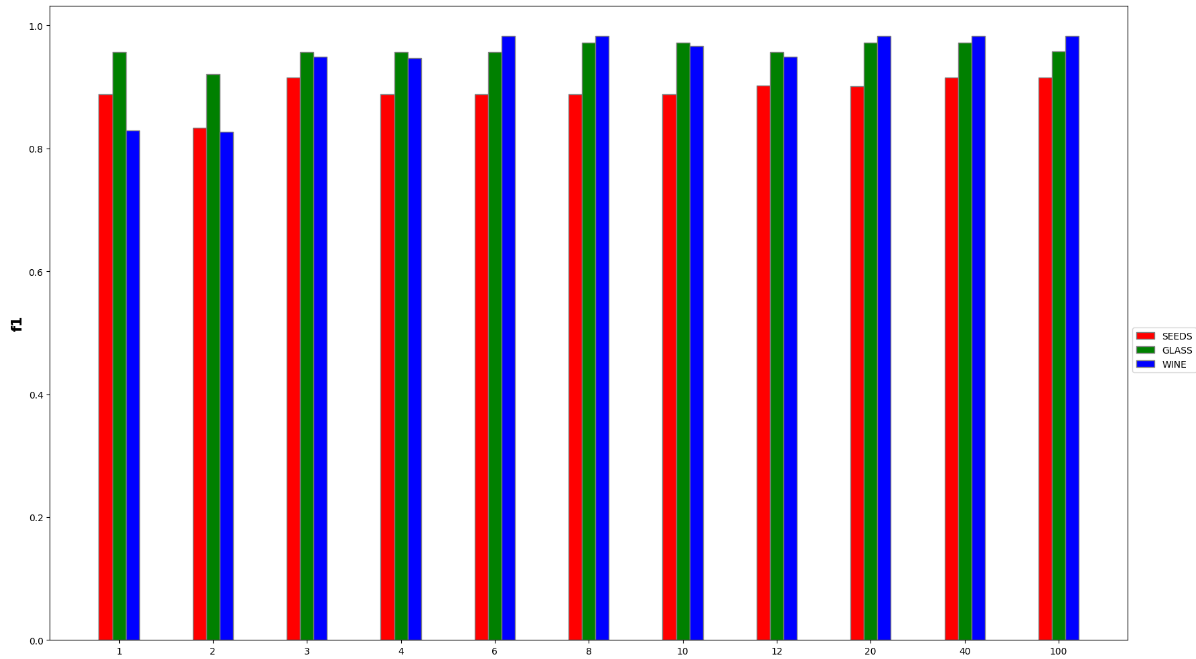


In [ ]:
```
metrics_list = ['f1']
dataset_list = ['SEEDS', 'GLASS', 'WINE']
colour_list = ['r', 'g', 'b']
```

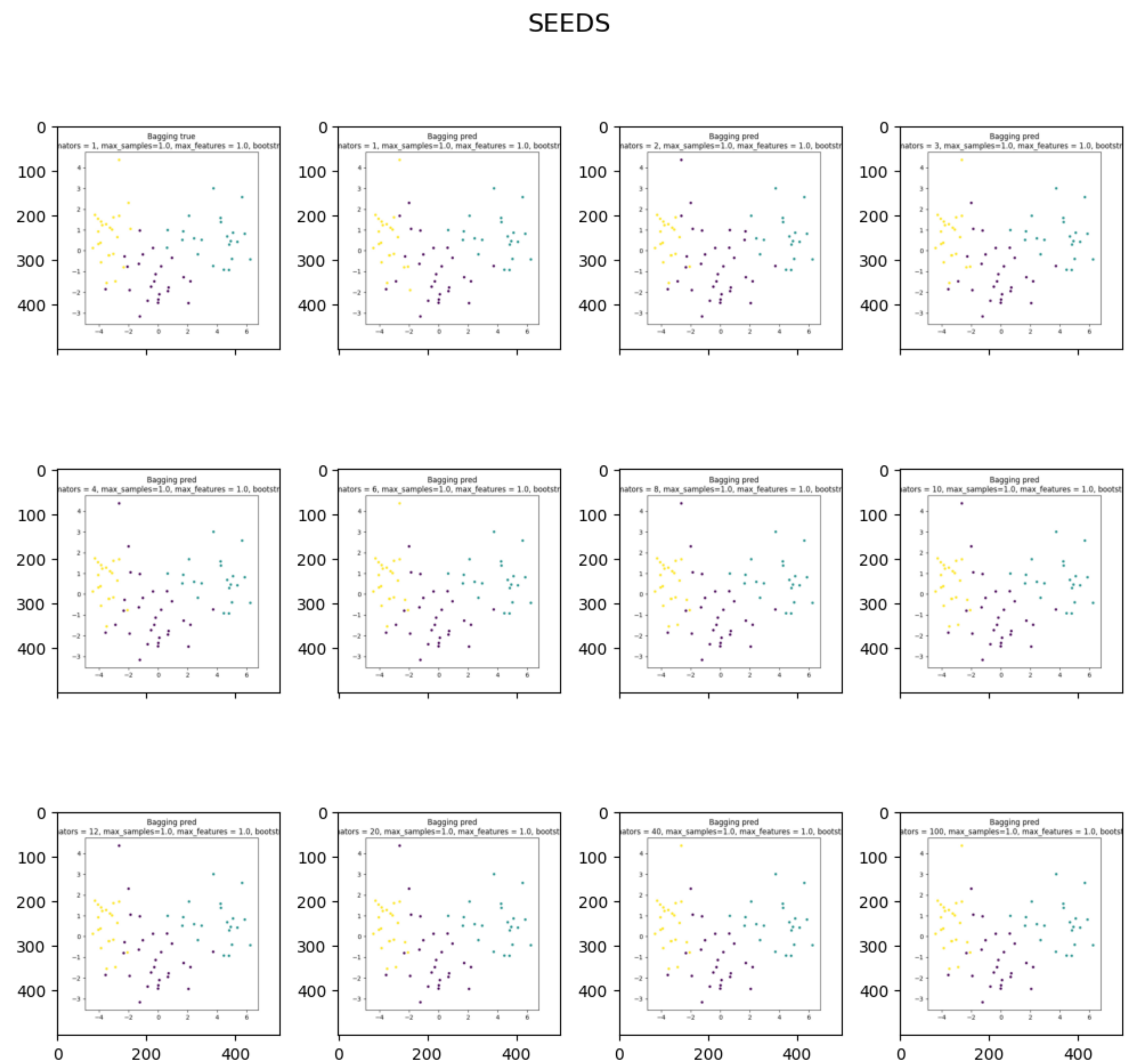
Bagging - liczba classfikatorow

In [ ]:
```
study_vals = [1, 2, 3, 4, 6, 8, 10, 12, 20, 40, 100]
results_list = [
[run_bagging (df_seeds, n_estimators = c) for c in study_vals],
[run_bagging (df_glass, n_estimators = c) for c in study_vals],
[run_bagging (df_wine, n_estimators = c) for c in study_vals],
]
```

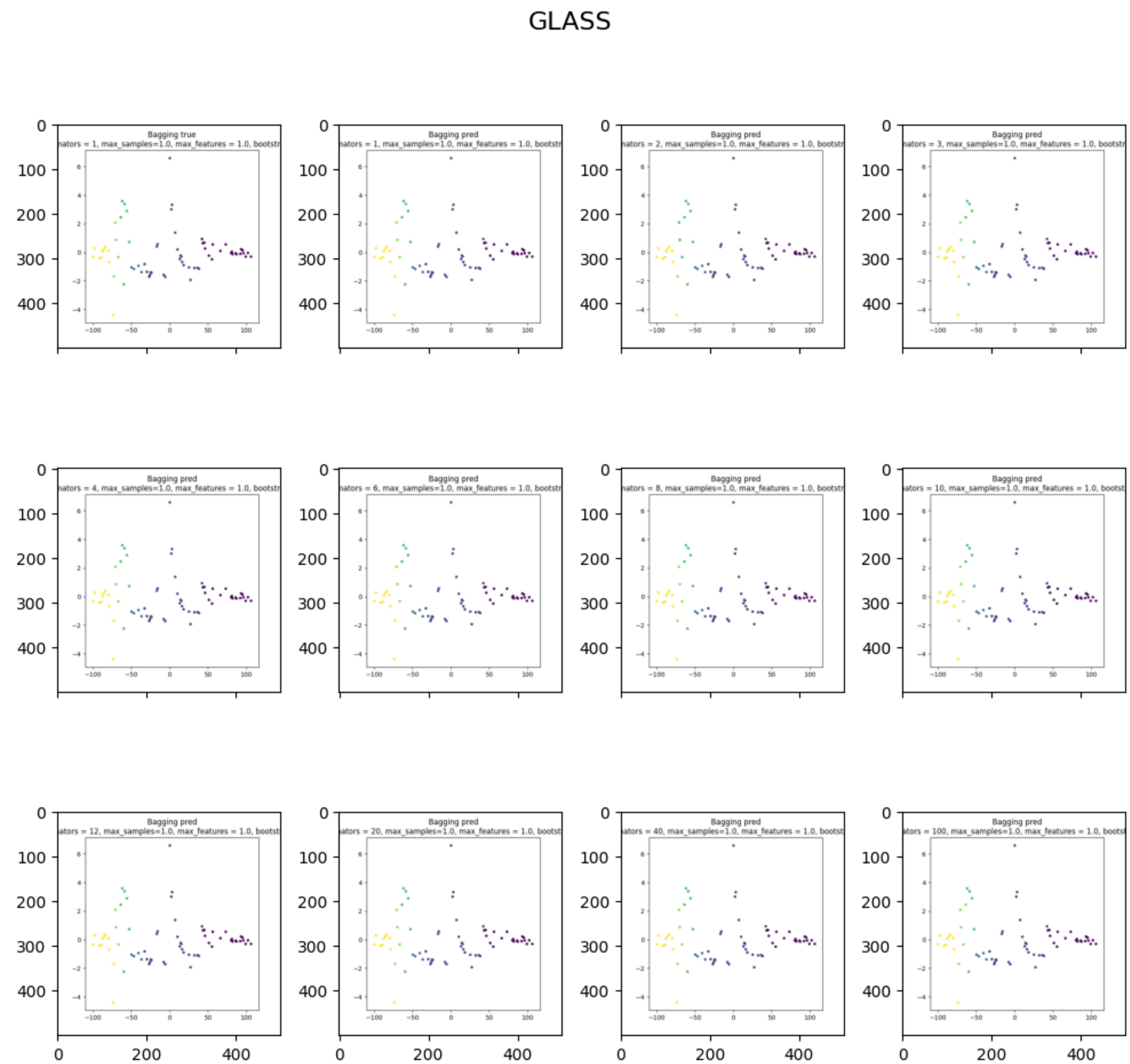
In [ ]:
```
plotStatistics(results_list, metrics_list, study_vals, dataset_list, colour_list)
```



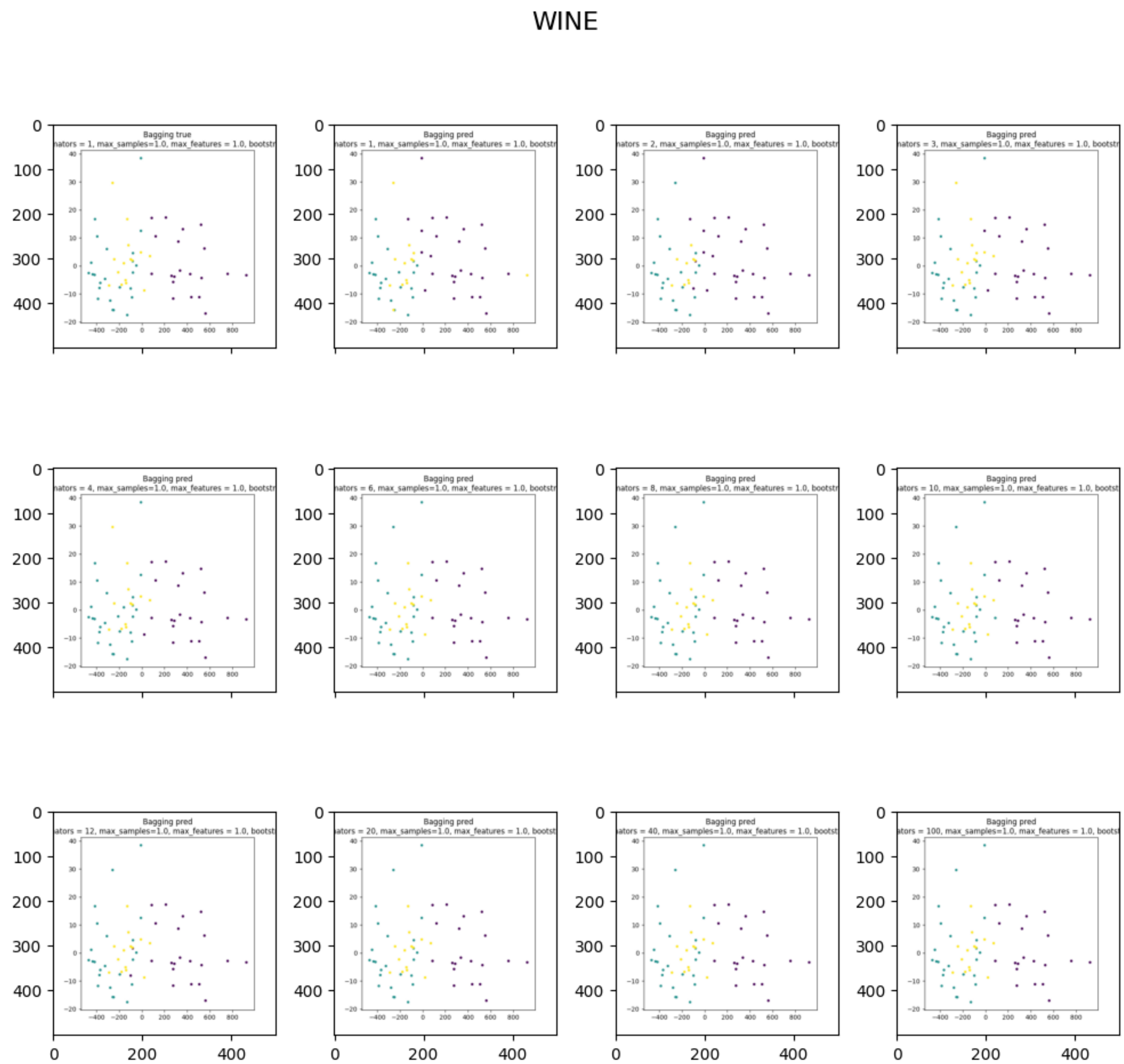
In [ ]:
```
combineFigsInOnePlot(results_list[0], dataset_list[0])
```



In [ ]:
```
combineFigsInOnePlot(results_list[1], dataset_list[1])
```



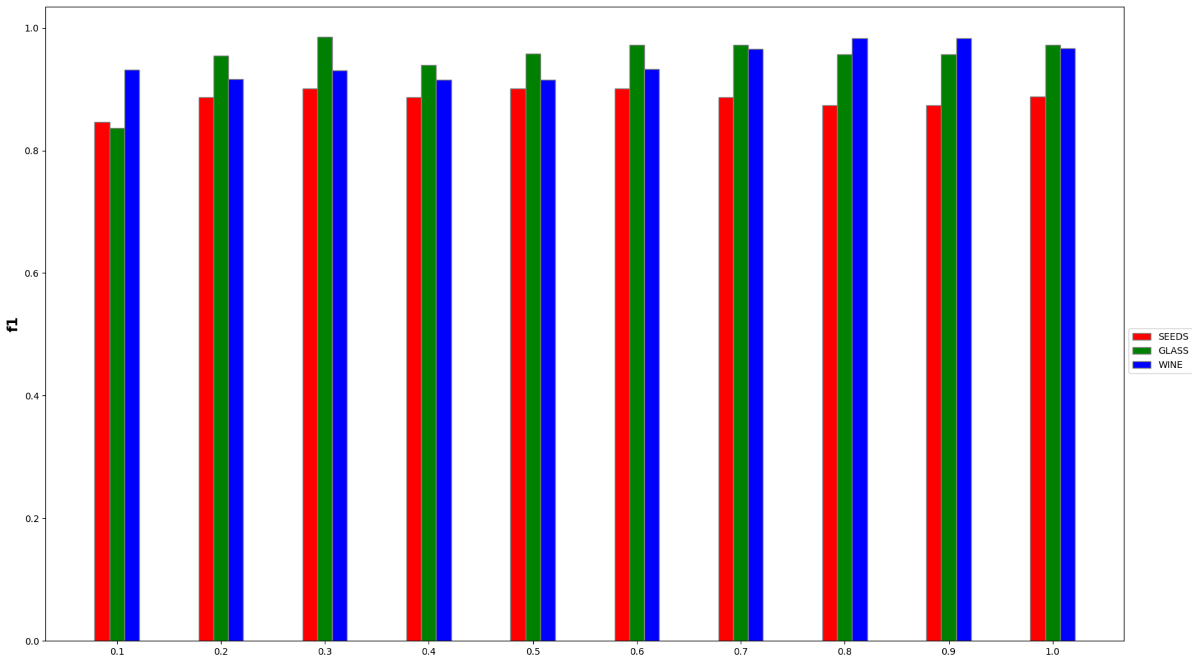
In [ ]:
```
combineFigsInOnePlot(results_list[2], dataset_list[2])
```



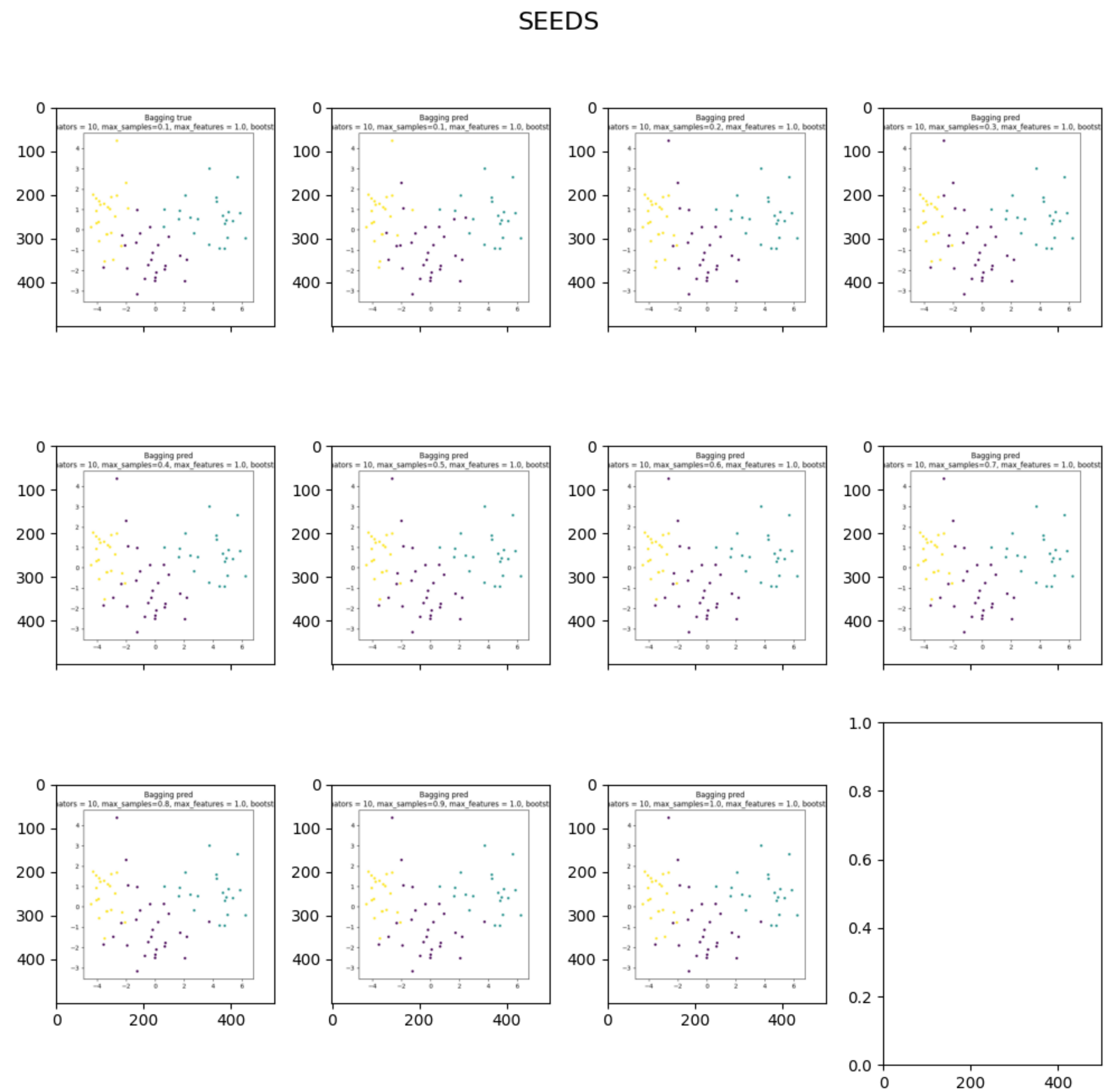
Bagging - liczba probek

In [ ]:
```
study_vals = [0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1.]
results_list = [
[run_bagging (df_seeds, max_samples = c) for c in study_vals],
[run_bagging (df_glass, max_samples = c) for c in study_vals],
[run_bagging (df_wine, max_samples = c) for c in study_vals],
]
```

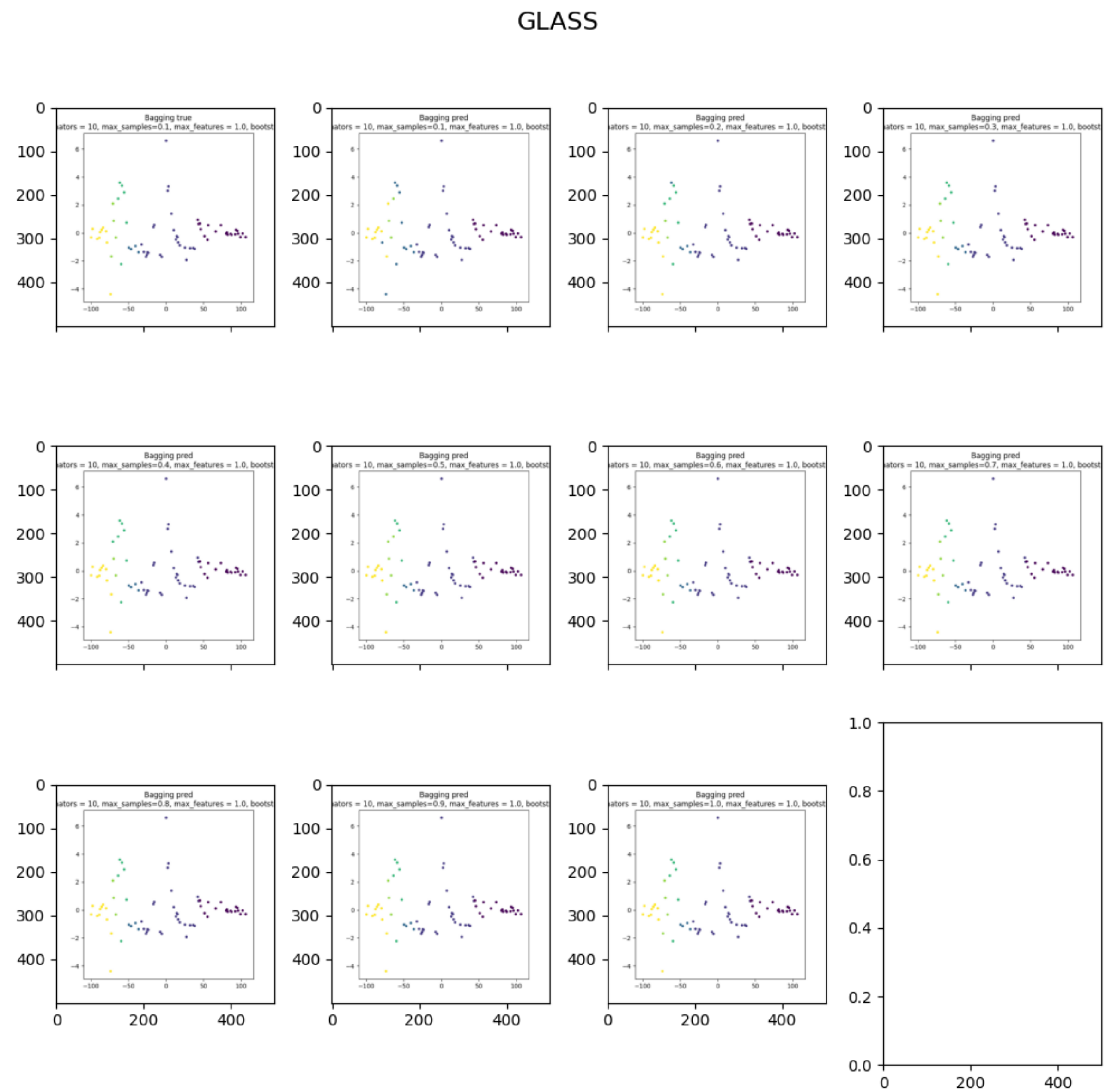
In [ ]:
```
plotStatistics(results_list, metrics_list, study_vals, dataset_list, colour_list)
```



In [ ]:
```
combineFigsInOnePlot(results_list[0], dataset_list[0])
```

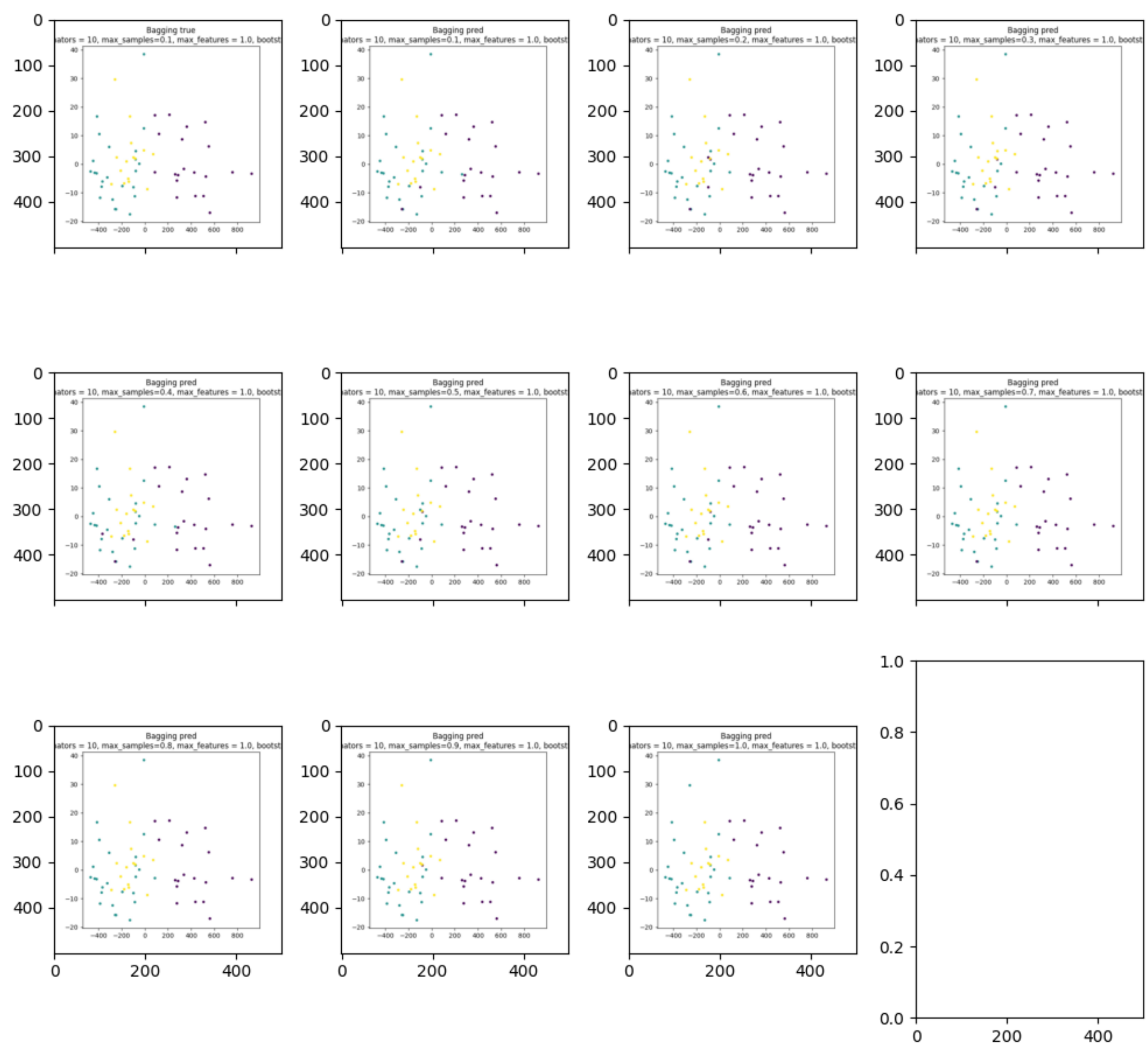


In [ ]:
```
combineFigsInOnePlot(results_list[1], dataset_list[1])
```




```
In [ ]: combineFigsInOnePlot(results_list[2], dataset_list[2])
```

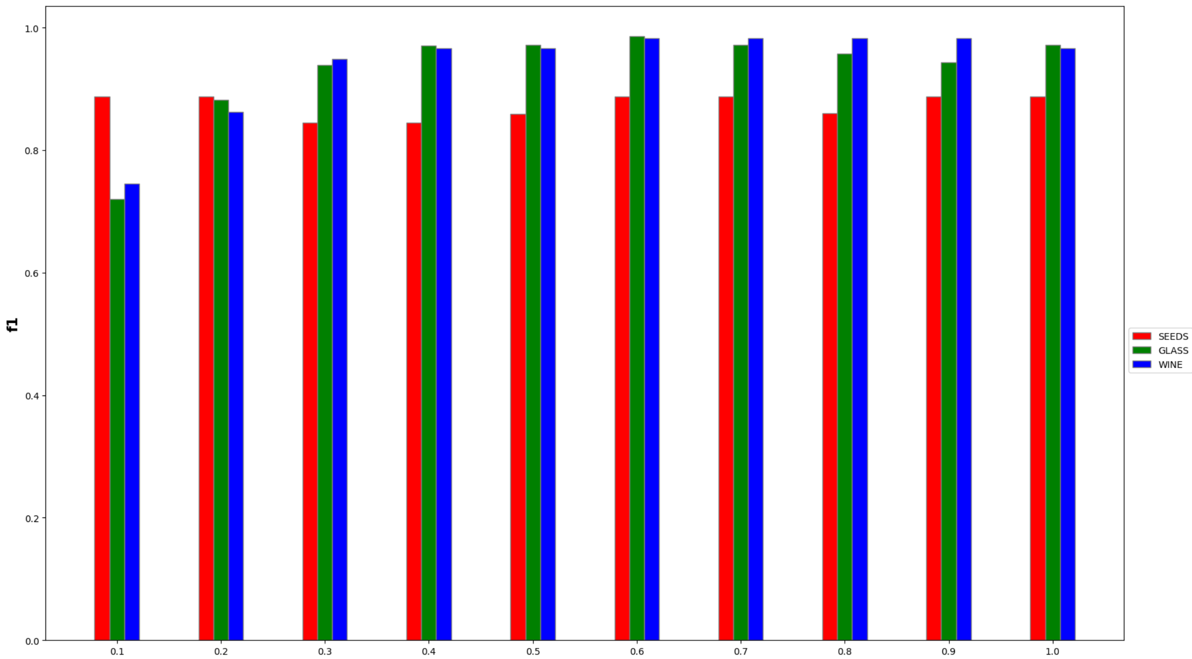
WINE



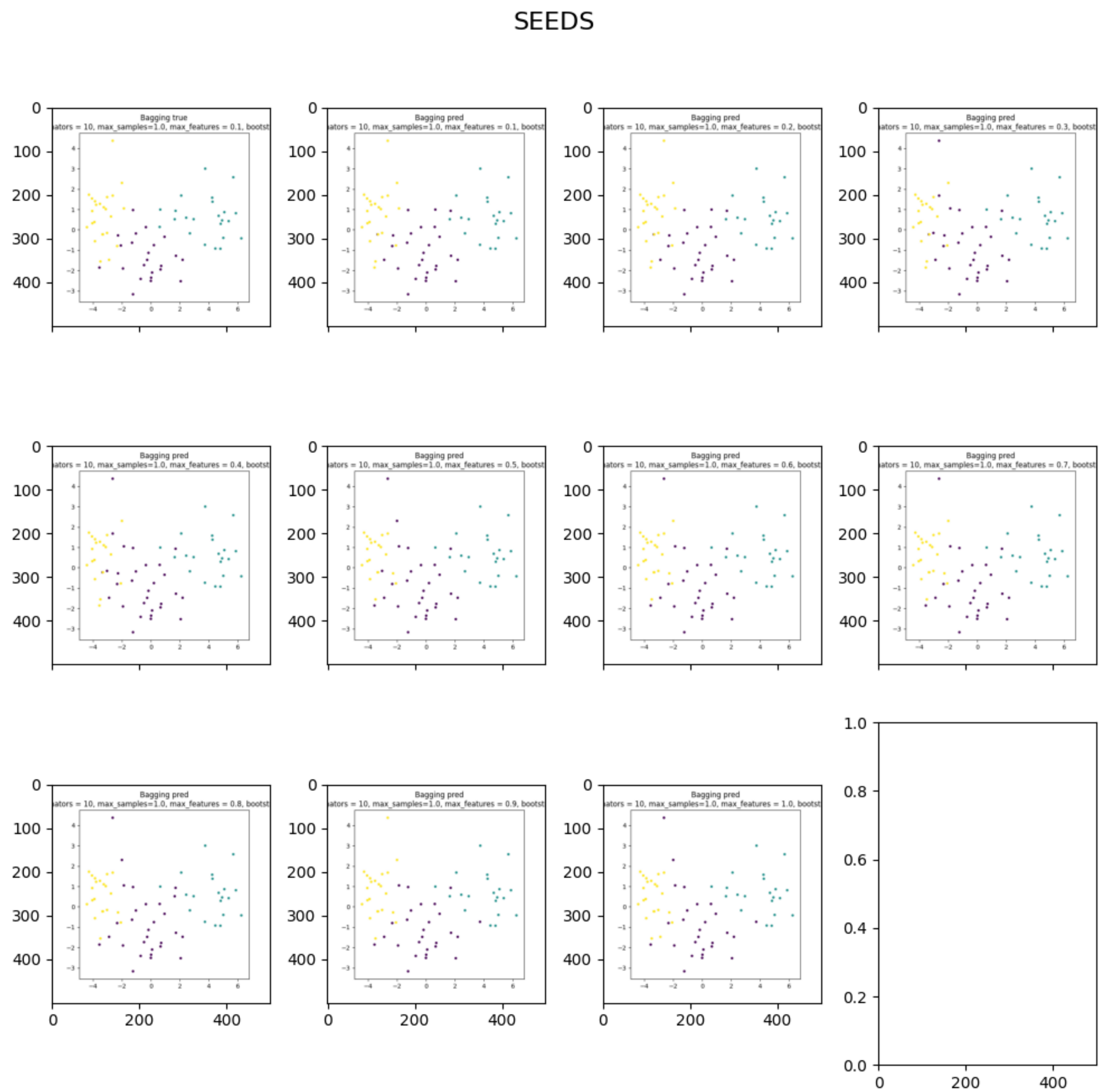
Bagging - liczba atrybutow

In [ ]:
```
study_vals = [0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1.]
results_list = [
[run_bagging (df_seeds, max_features = c) for c in study_vals],
[run_bagging (df_glass, max_features = c) for c in study_vals],
[run_bagging (df_wine, max_features = c) for c in study_vals],
]
```

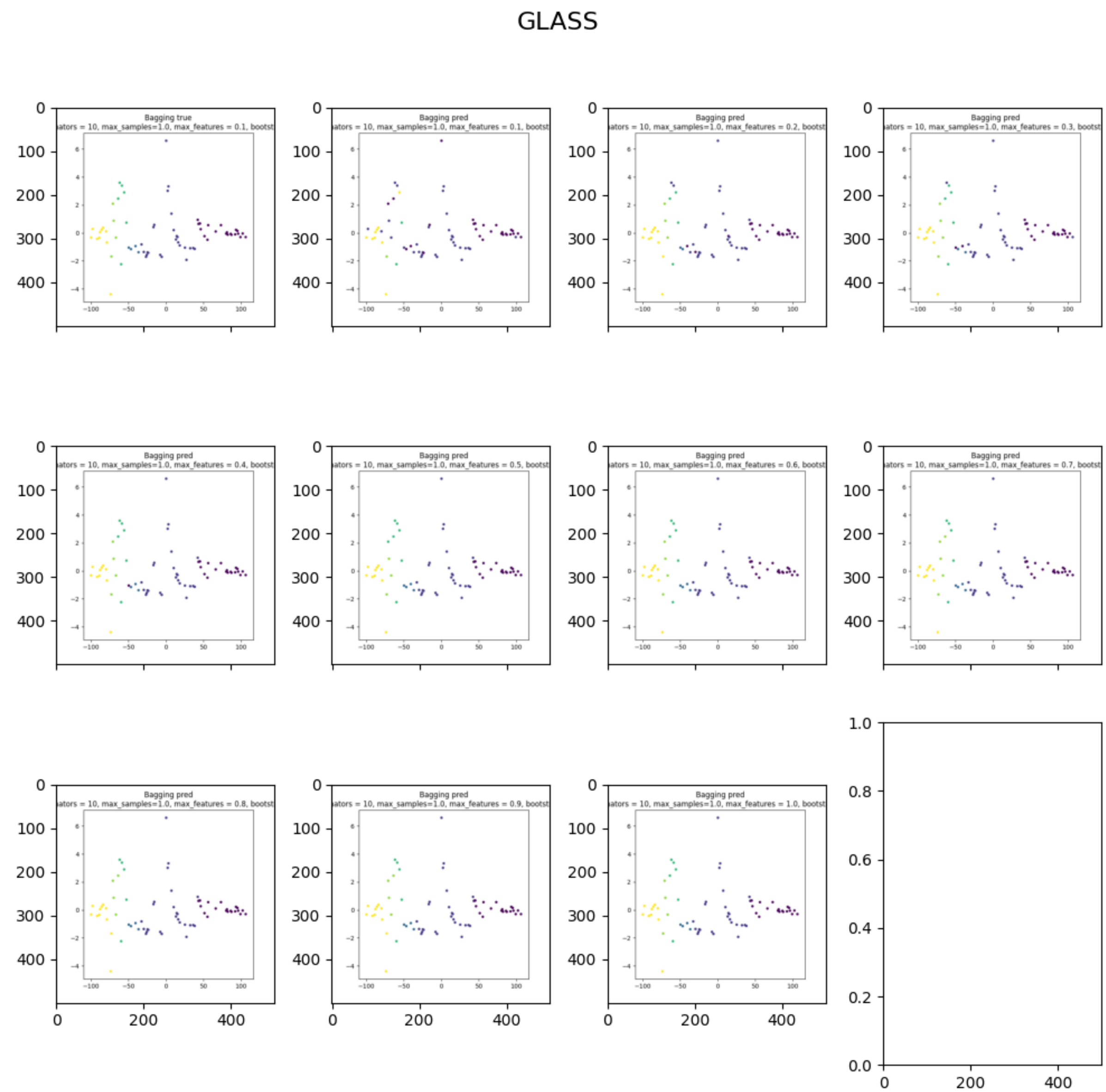
In [ ]:
```
plotStatistics(results_list, metrics_list, study_vals, dataset_list, colour_list)
```



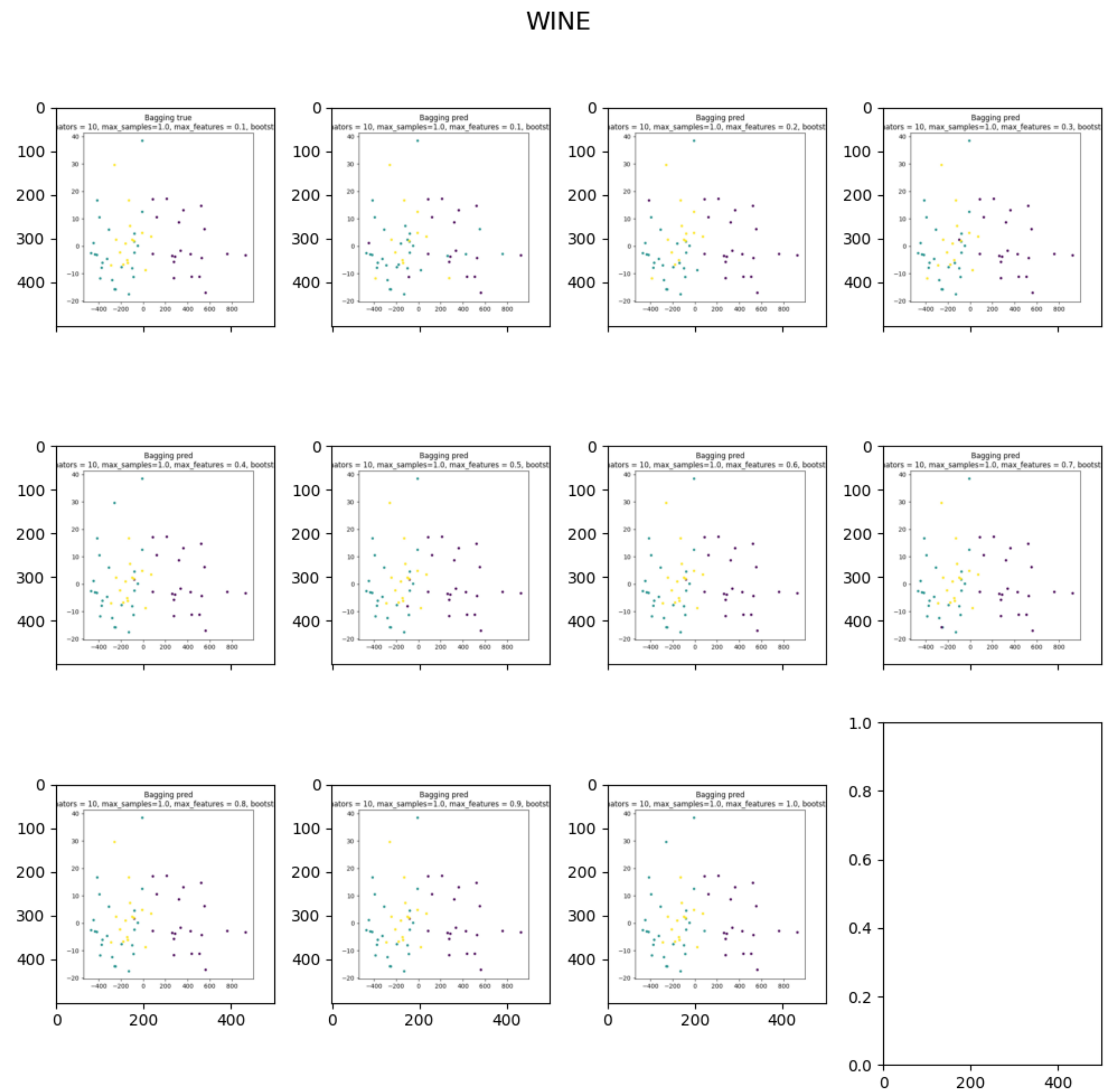
In [ ]:
```
combineFigsInOnePlot(results_list[0], dataset_list[0])
```



In [ ]:
```
combineFigsInOnePlot(results_list[1], dataset_list[1])
```



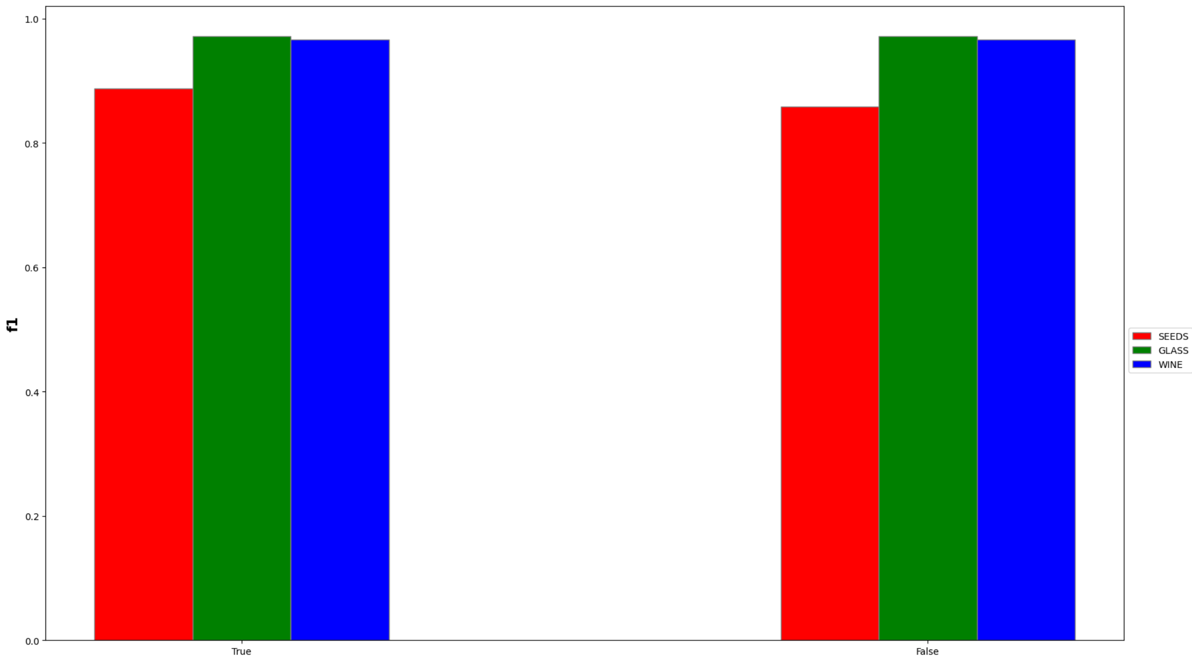

```
In [ ]: combineFigsInOnePlot(results_list[2], dataset_list[2])
```



Bagging - bootstrap

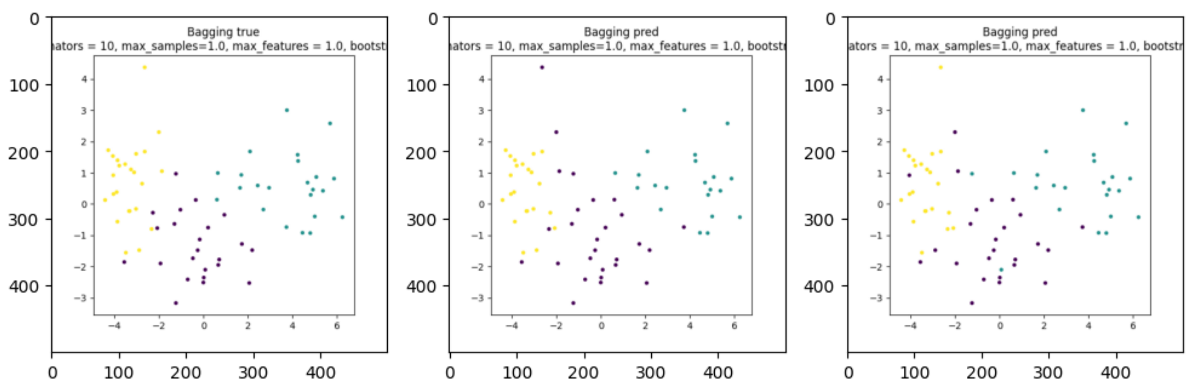
In [ ]:
```
study_vals = [True, False]
results_list = [
[run_bagging (df_seeds, bootstrap = c) for c in study_vals],
[run_bagging (df_glass, bootstrap = c) for c in study_vals],
[run_bagging (df_wine, bootstrap = c) for c in study_vals],
]
```

In [ ]:
```
plotStatistics(results_list, metrics_list, study_vals, dataset_list, colour_list)
```



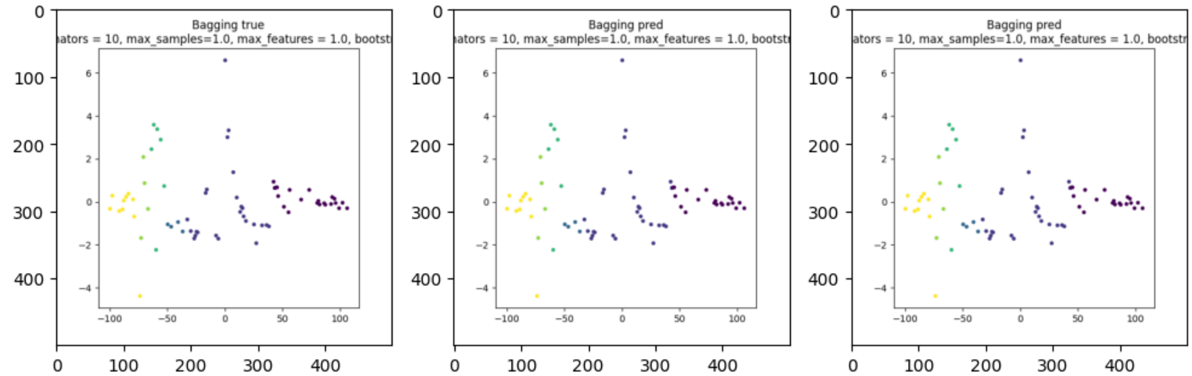
In [ ]:
```
combineFigsInOnePlot(results_list[0], dataset_list[0])
```

SEEDS



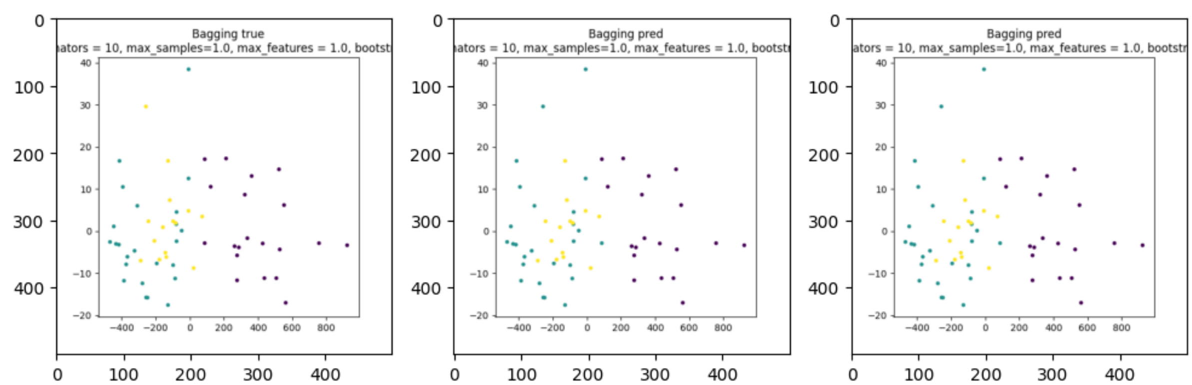
In [ ]:
```
combineFigsInOnePlot(results_list[1], dataset_list[1])
```

GLASS



In [ ]:
```
combineFigsInOnePlot(results_list[2], dataset_list[2])
```

WINE

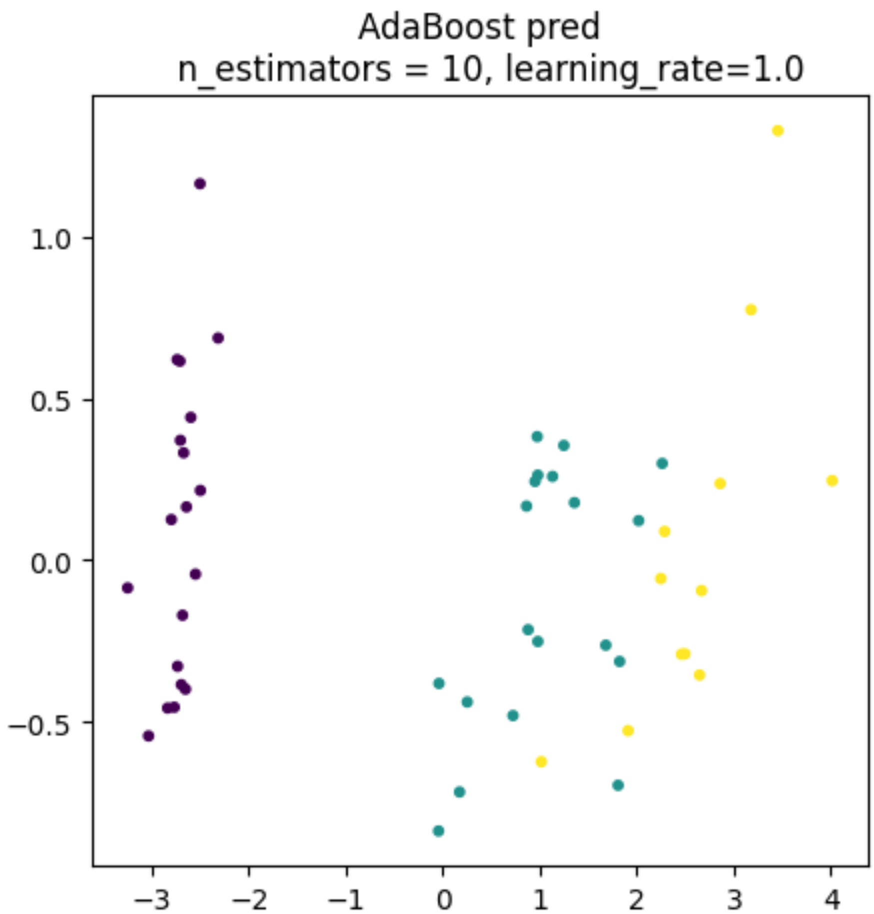


Boosting

In [ ]:
```
from sklearn.metrics import f1_score
from sklearn.cluster import KMeans
from sklearn.pipeline import Pipeline
from sklearn.impute import SimpleImputer
from sklearn.preprocessing import StandardScaler
import numpy as np
from sklearn.ensemble import AdaBoostClassifier

def run_adaboost(df, n_estimators = 10, learning_rate = 1.0):
    df_train, df_test = train_test_split( df, test_size=0.33, random_state=42)
    clf = AdaBoostClassifier(n_estimators = n_estimators, learning_rate = learning_
    clf = Pipeline([('imputate', SimpleImputer( strategy='mean')),
                    ('standardization', StandardScaler()),
                    ('clf', clf),])

    clf.fit(df_train.iloc[:, :-1], df_train.iloc[:, -1])

    y_true = df_test.iloc[:, -1].tolist()
    y_pred = clf.predict(df_test.iloc[:, :-1])

    X_reduced = PCA(n_components=2).fit_transform(df_test)

    pred_fig = plt.figure(1, figsize=(5, 5))
    ax1 = pred_fig.add_subplot()
    ax1.scatter(X_reduced[:, 0], X_reduced[:, 1], s=10, c=y_pred)
    ax1.set_title(f"AdaBoost pred\n  n_estimators = {n_estimators}, learning_rate={
    plt.close()

    true_fig = plt.figure(2, figsize=(5, 5))
    ax2 = true_fig.add_subplot()
    ax2.scatter(X_reduced[:, 0], X_reduced[:, 1], s=10, c=y_true)
    ax2.set_title(f"AdaBoost true\n  n_estimators = {n_estimators}, learning_rate={
    plt.close()

    f1 = f1_score(y_true, y_pred, average='weighted')

    return {'f1':f1,
            'pred_fig': pred_fig, 'true_fig': true_fig,}

test_run = run_adaboost(df_iris)
print(test_run['f1'])
test_run['pred_fig']
```

```
0.8784873949579831
```

Out[ ]:



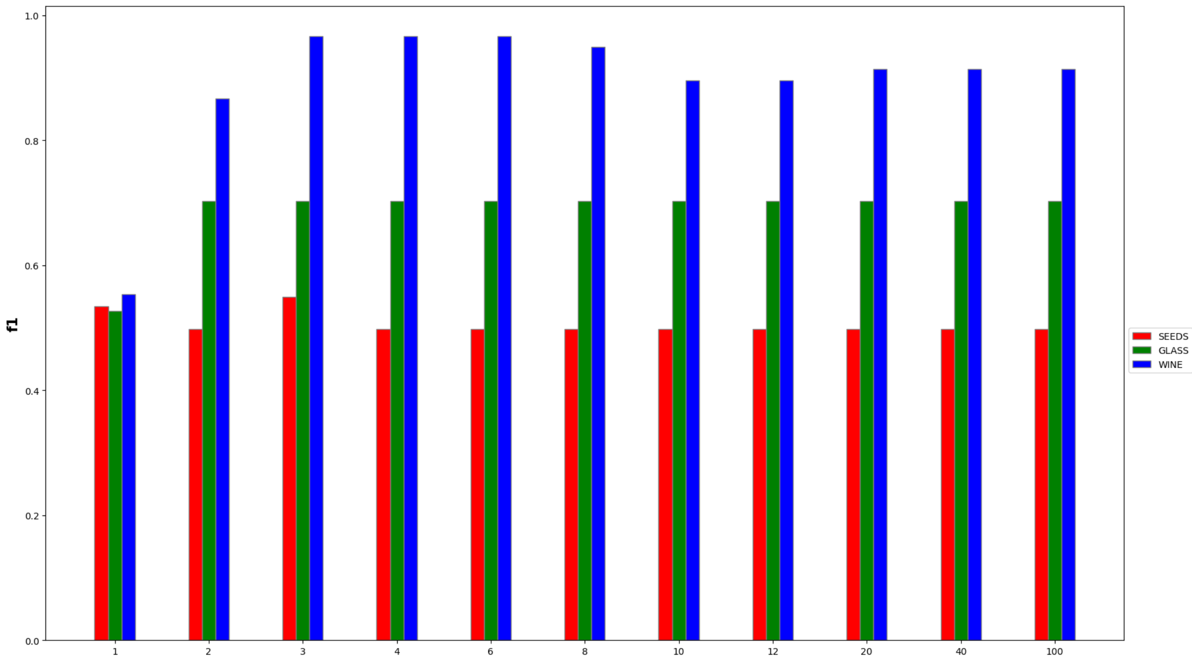
AdaBoost - liczba klasyfikatorow

In [ ]:

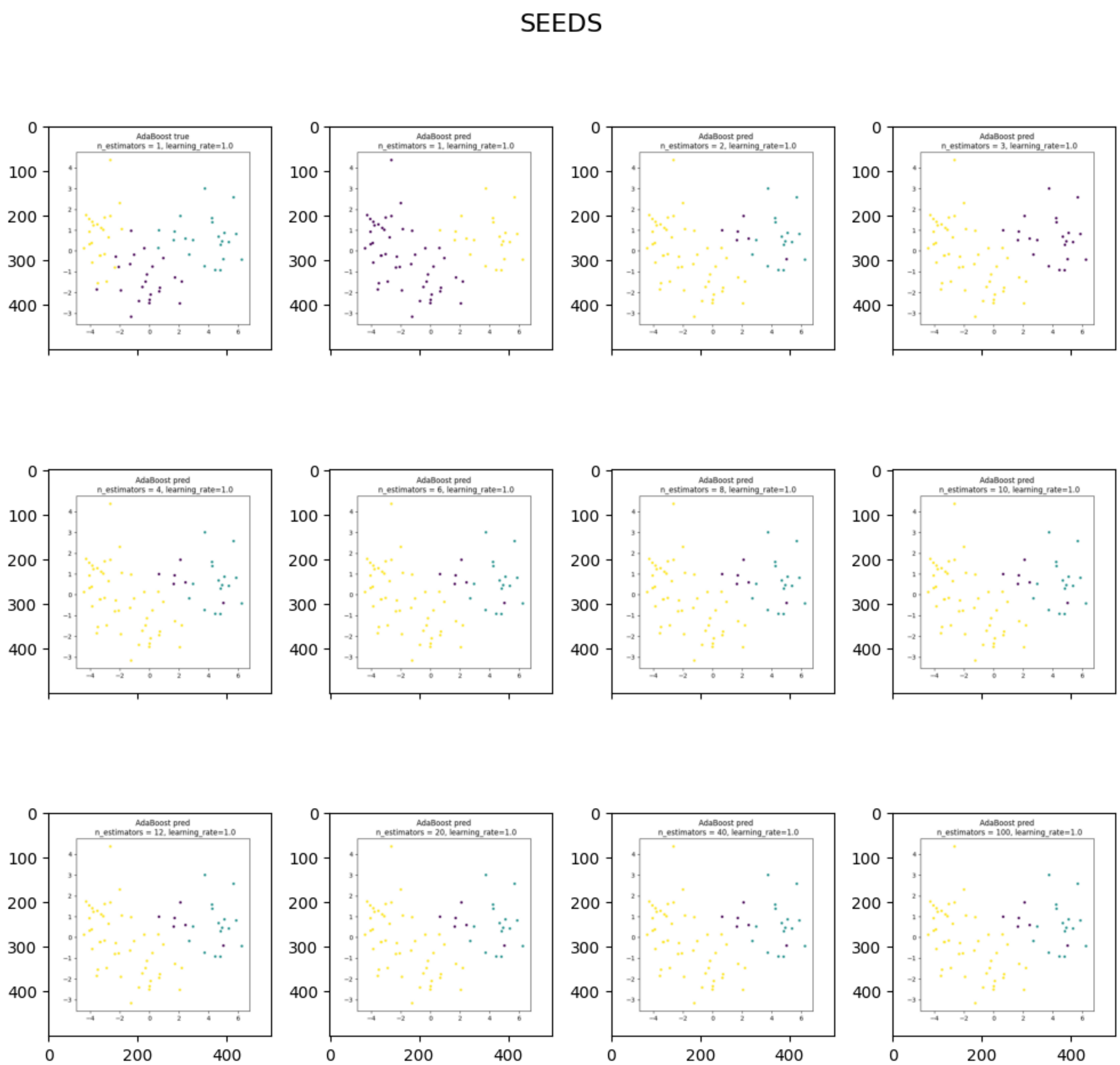
```
study_vals = [1, 2, 3, 4, 6, 8, 10, 12, 20, 40, 100]
results_list = [
[run_adaboost (df_seeds, n_estimators = c) for c in study_vals],
[run_adaboost (df_glass, n_estimators = c) for c in study_vals],
[run_adaboost (df_wine, n_estimators = c) for c in study_vals],
]
```

In [ ]:

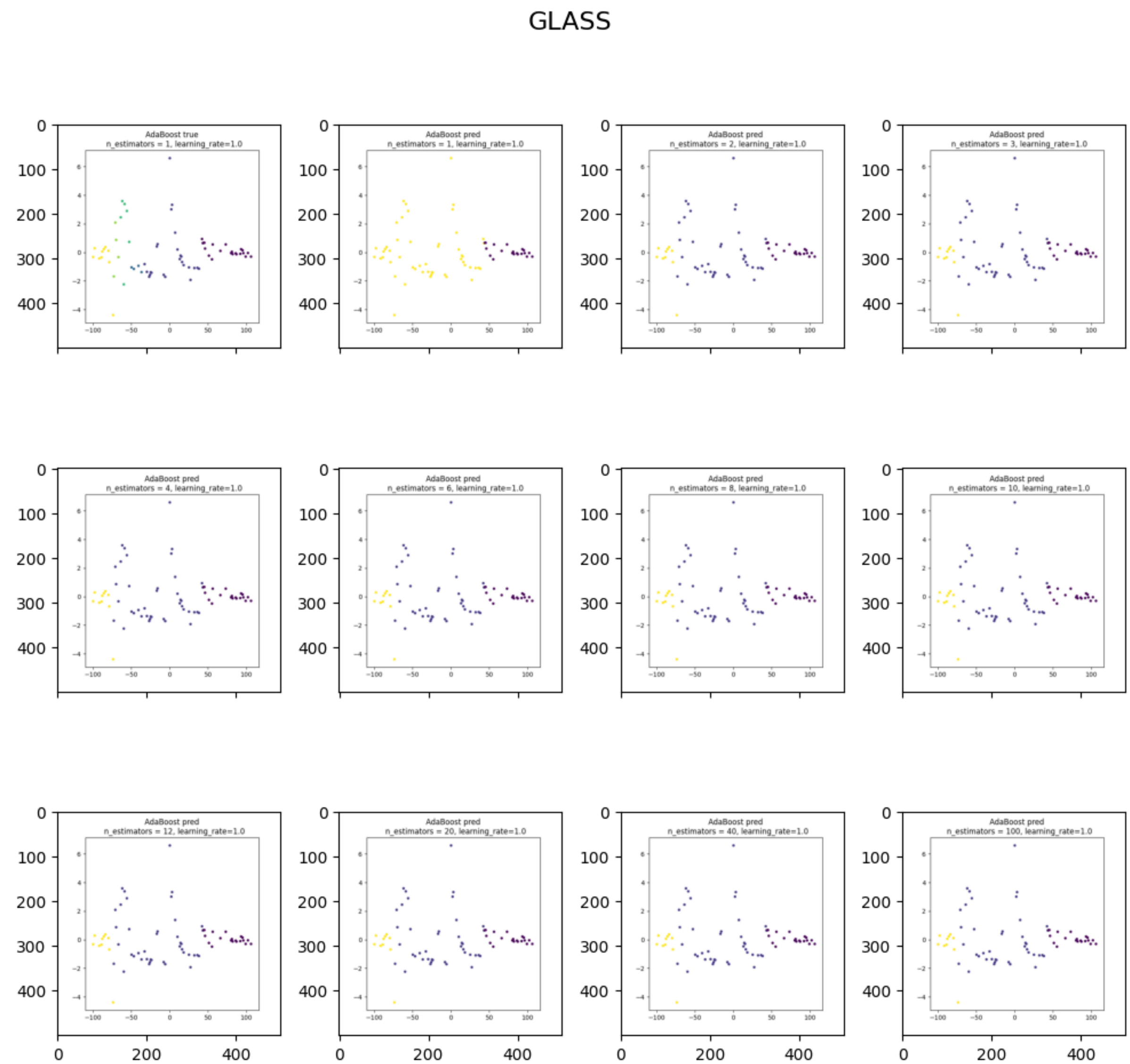
```
plotStatistics(results_list, metrics_list, study_vals, dataset_list, colour_list)
```



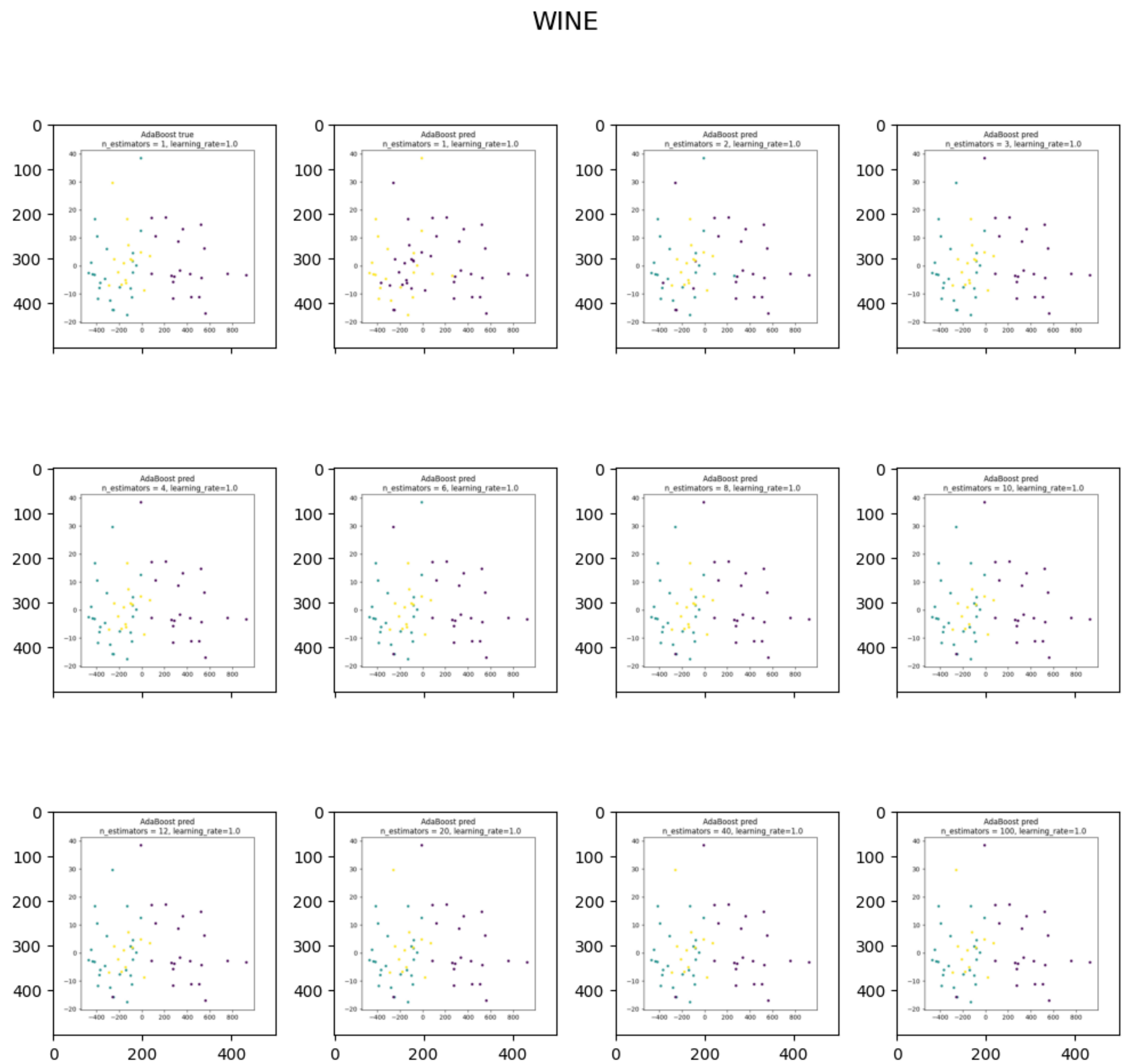
In [ ]:
```
combineFigsInOnePlot(results_list[0], dataset_list[0])
```



In [ ]:
```
combineFigsInOnePlot(results_list[1], dataset_list[1])
```



In [ ]:
```
combineFigsInOnePlot(results_list[2], dataset_list[2])
```



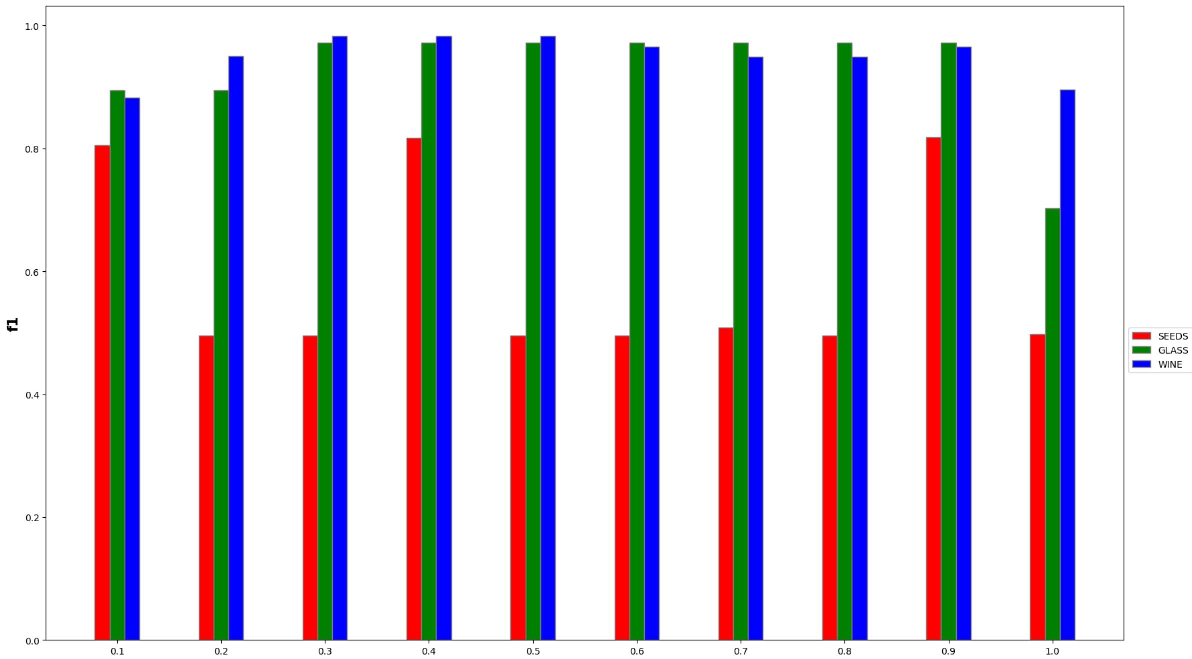
AdaBoost - wspl uczenia

In [ ]:

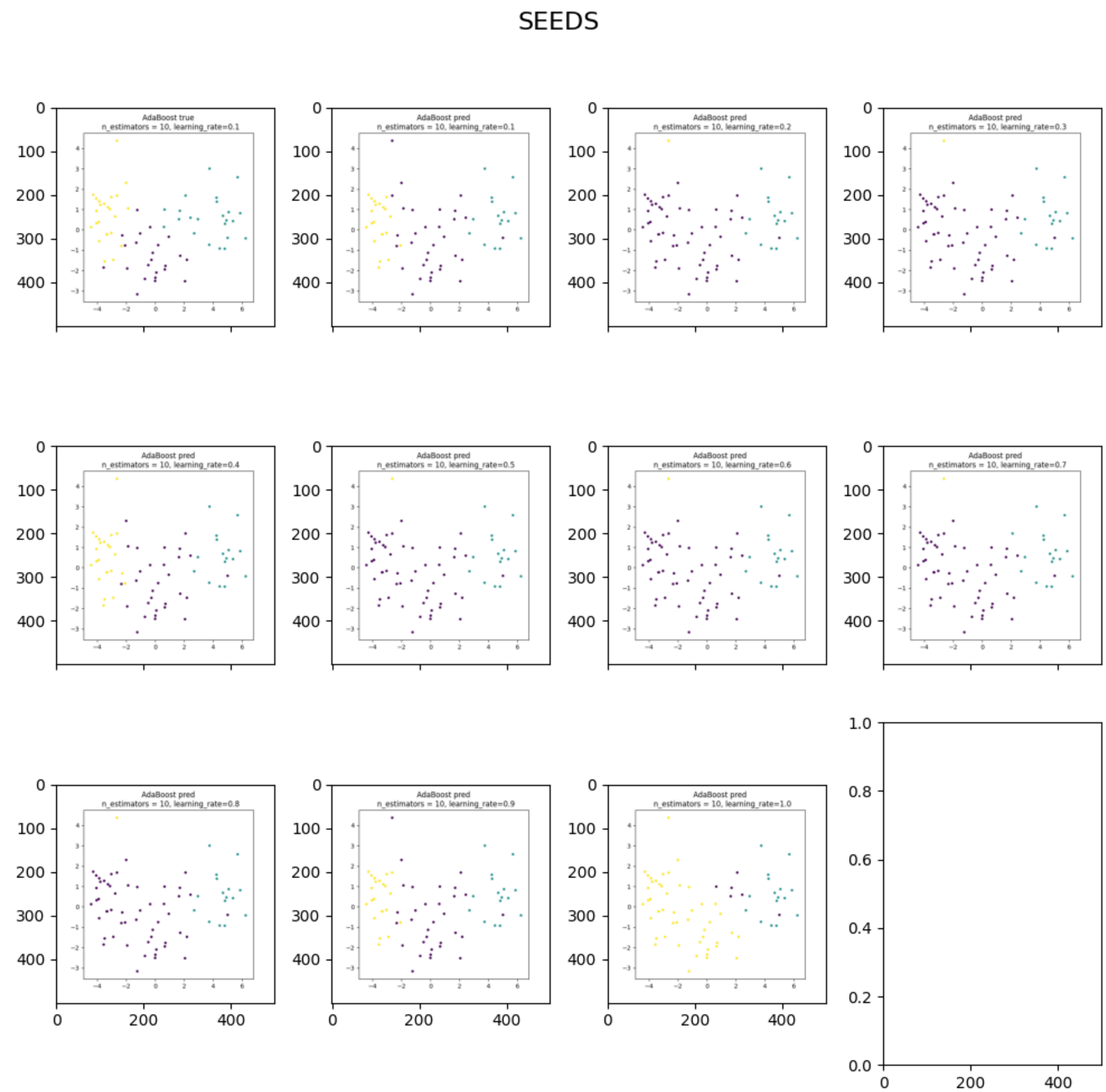
```
study_vals = [0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1.]
results_list = [
[run_adaboost (df_seeds, learning_rate = c) for c in study_vals],
[run_adaboost (df_glass, learning_rate = c) for c in study_vals],
[run_adaboost (df_wine, learning_rate = c) for c in study_vals],
]
```

In [ ]:

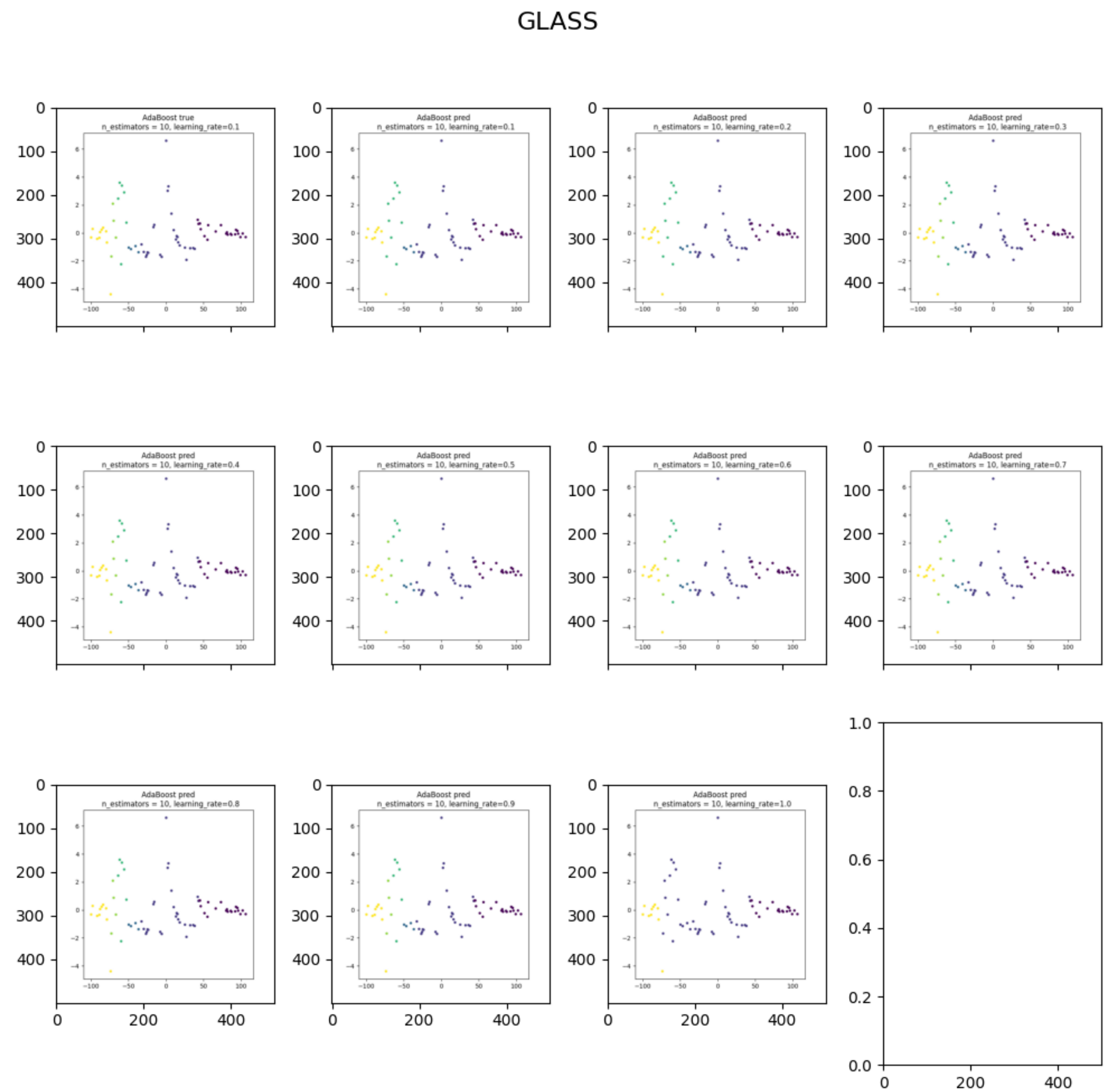
```
plotStatistics(results_list, metrics_list, study_vals, dataset_list, colour_list)
```



In [ ]:
```
combineFigsInOnePlot(results_list[0], dataset_list[0])
```

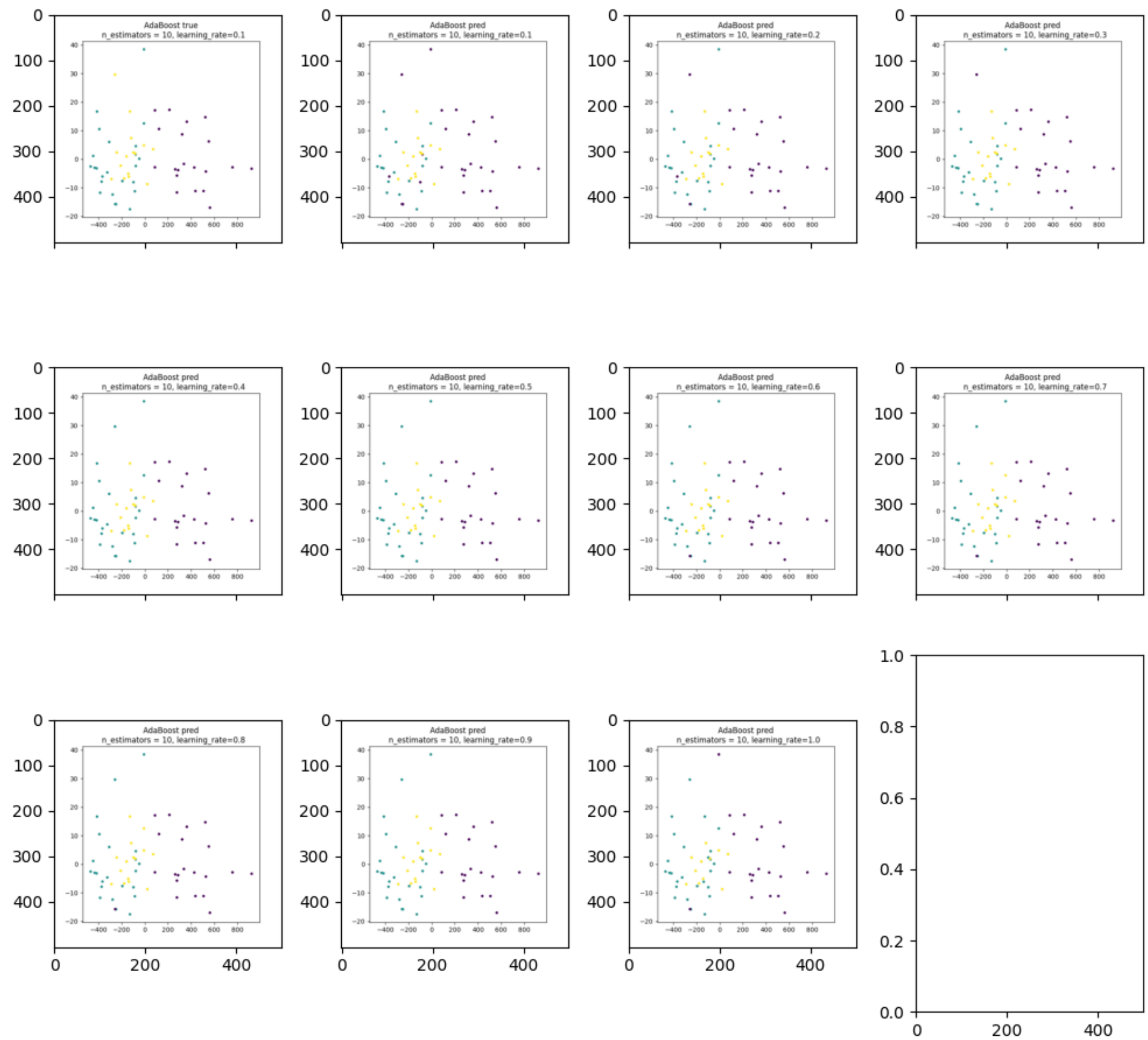


In [ ]:
```
combineFigsInOnePlot(results_list[1], dataset_list[1])
```



In [ ]:
```
combineFigsInOnePlot(results_list[2], dataset_list[2])
```

WINE

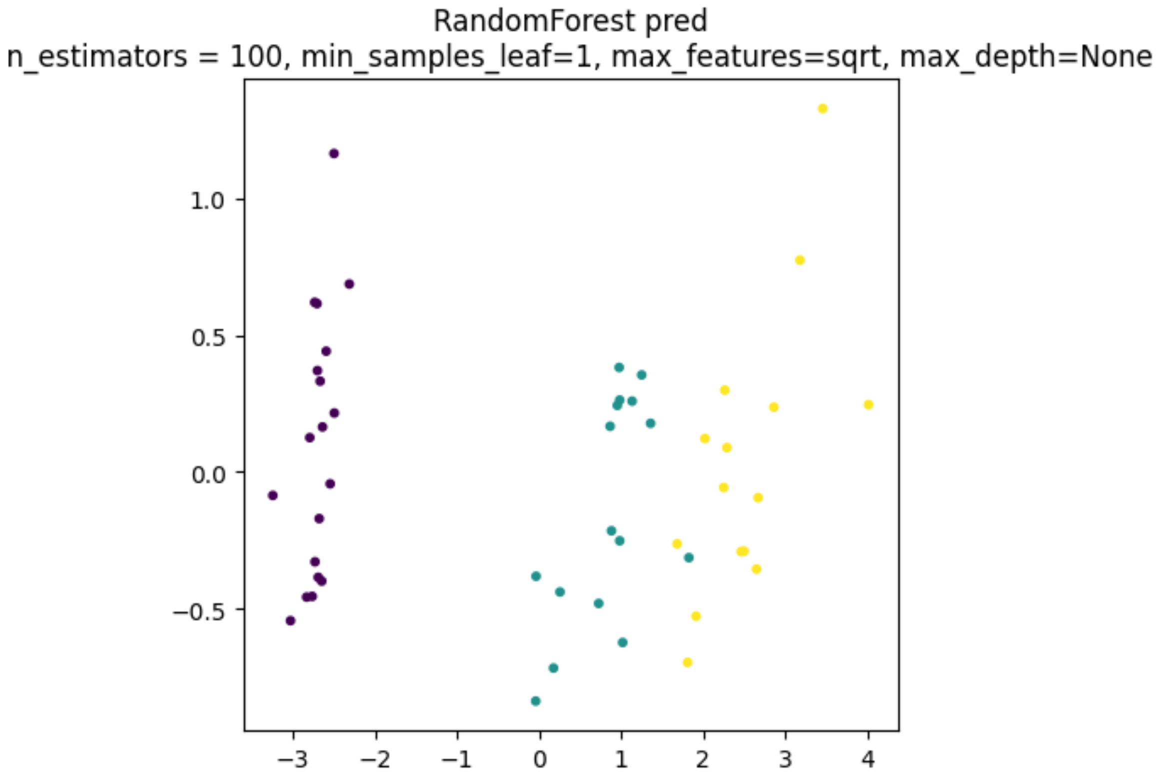


Random forest

In [ ]:
```
from sklearn.metrics import f1_score
from sklearn.cluster import KMeans
from sklearn.pipeline import Pipeline
from sklearn.impute import SimpleImputer
from sklearn.preprocessing import StandardScaler
import numpy as np
from sklearn.ensemble import RandomForestClassifier

def run_random_forest(df, n_estimators = 100, min_samples_leaf = 1, max_features ='
    df_train, df_test = train_test_split( df, test_size=0.33, random_state=42)
    clf = RandomForestClassifier(n_estimators = n_estimators, min_samples_leaf = mi
                                 max_features = max_features,  max_depth = max_depth, r
    clf = Pipeline([('imputate', SimpleImputer( strategy='mean')),
                    ('standardization', StandardScaler()),
                    ('clf', clf),])

    clf.fit(df_train.iloc[:, :-1], df_train.iloc[:, -1])

    y_true = df_test.iloc[:, -1].tolist()
    y_pred = clf.predict(df_test.iloc[:, :-1])

    X_reduced = PCA(n_components=2).fit_transform(df_test)

    pred_fig = plt.figure(1, figsize=(5, 5))
    ax1 = pred_fig.add_subplot()
    ax1.scatter(X_reduced[:, 0], X_reduced[:, 1], s=10, c=y_pred)
    ax1.set_title(f"RandomForest pred\n  n_estimators = {n_estimators}, min_samples
    plt.close()

    true_fig = plt.figure(2, figsize=(5, 5))
    ax2 = true_fig.add_subplot()
    ax2.scatter(X_reduced[:, 0], X_reduced[:, 1], s=10, c=y_true)
    ax2.set_title(f"RandomForest true\n  n_estimators = {n_estimators}, min_samples
    plt.close()

    f1 = f1_score(y_true, y_pred, average='weighted')

    return {'f1':f1,
            'pred_fig': pred_fig, 'true_fig': true_fig,}

test_run = run_random_forest(df_iris)
print(test_run['f1'])
test_run['pred_fig']
```

```
0.98
```

Out[ ]:



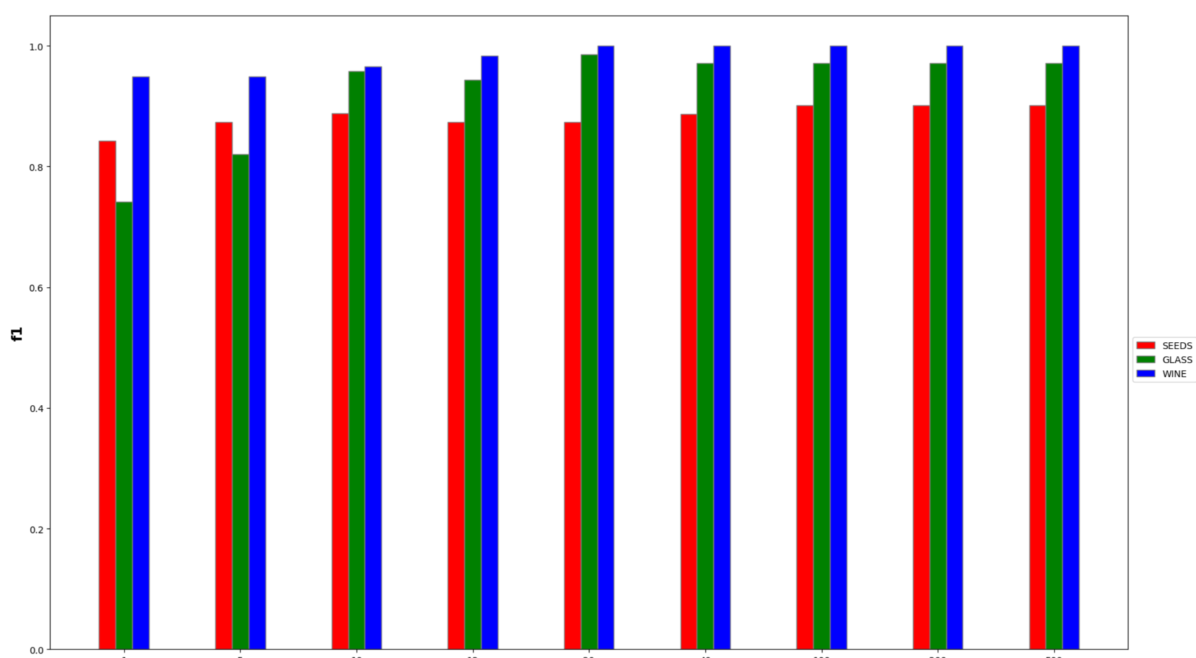
Random forest - liczba drzew

In [ ]:

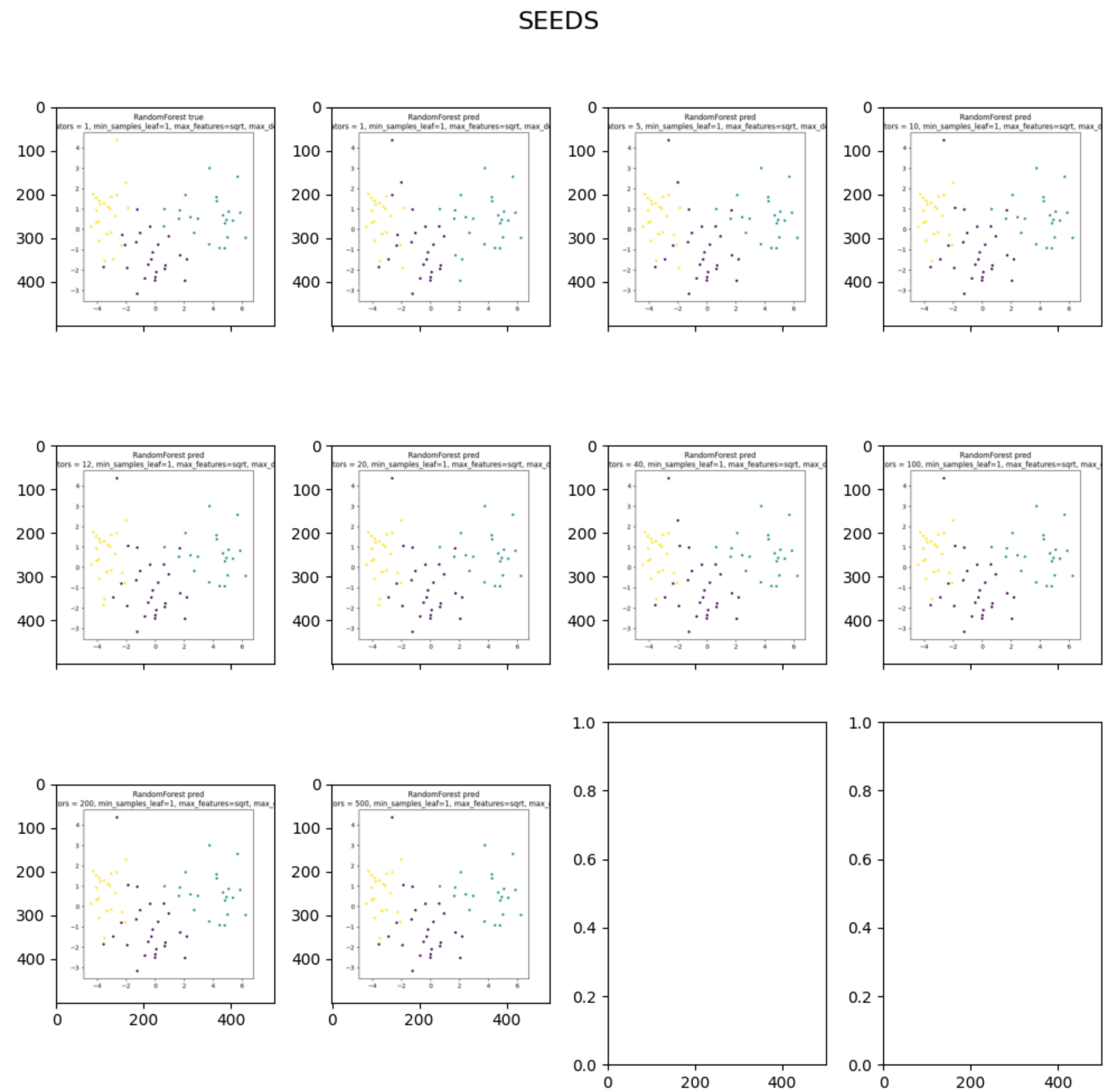
```
study_vals = [1, 5, 10, 12, 20, 40, 100, 200, 500]
results_list = [
[run_random_forest (df_seeds, n_estimators = c) for c in study_vals],
[run_random_forest (df_glass, n_estimators = c) for c in study_vals],
[run_random_forest (df_wine, n_estimators = c) for c in study_vals],
]
```

In [ ]:

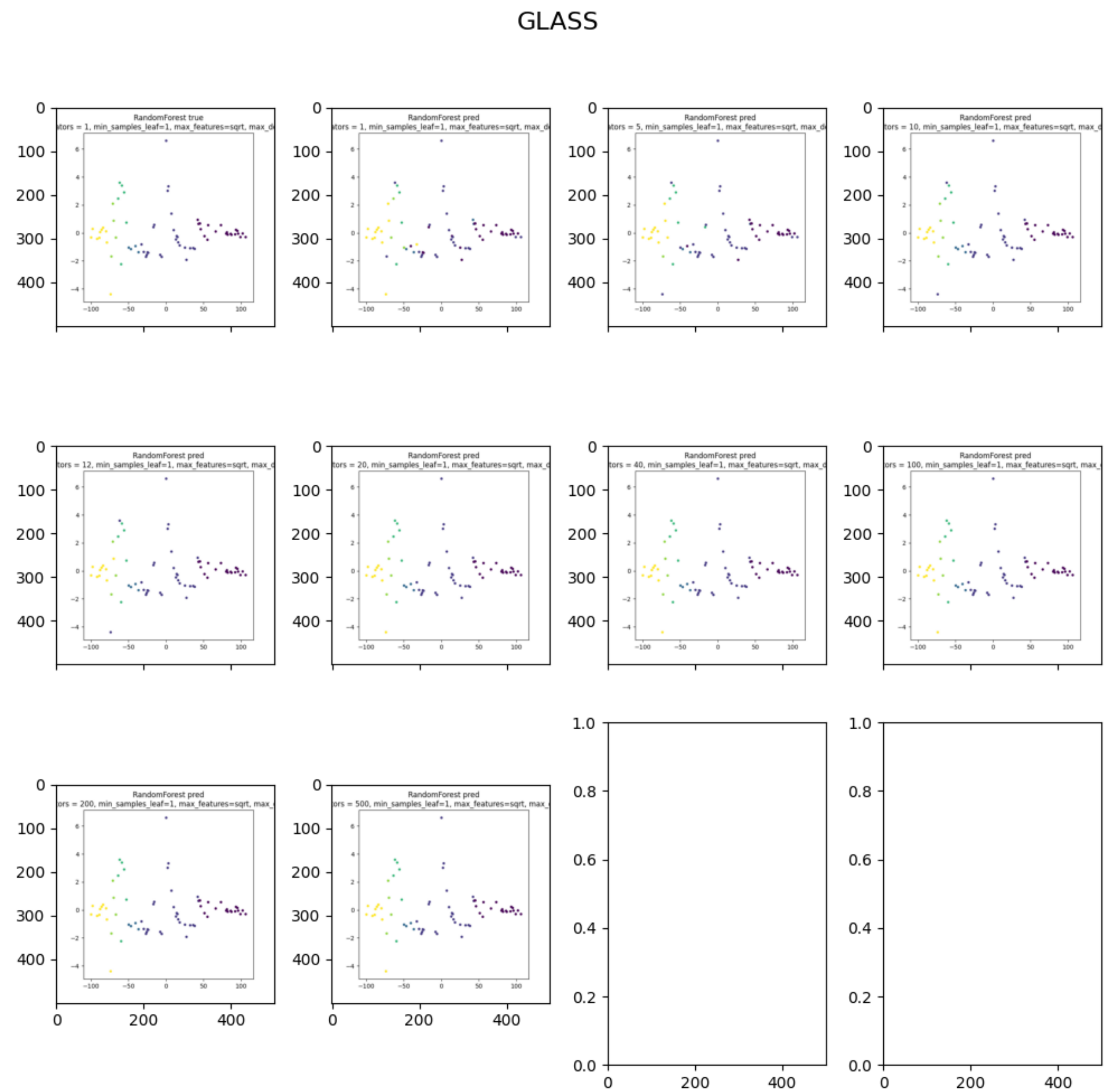
```
plotStatistics(results_list, metrics_list, study_vals, dataset_list, colour_list)
```



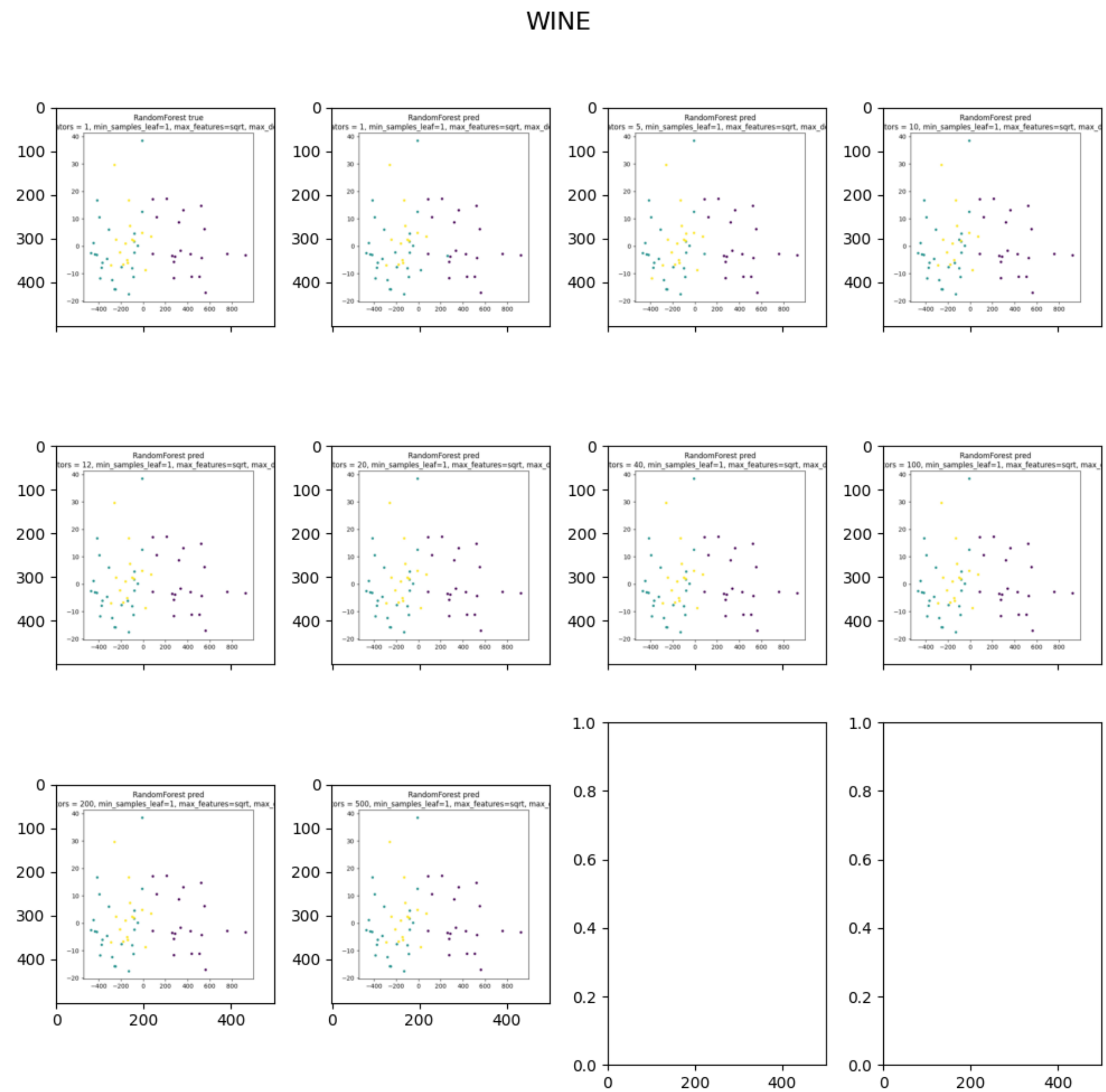
In [ ]:
```
combineFigsInOnePlot(results_list[0], dataset_list[0])
```



In [ ]:
```
combineFigsInOnePlot(results_list[1], dataset_list[1])
```



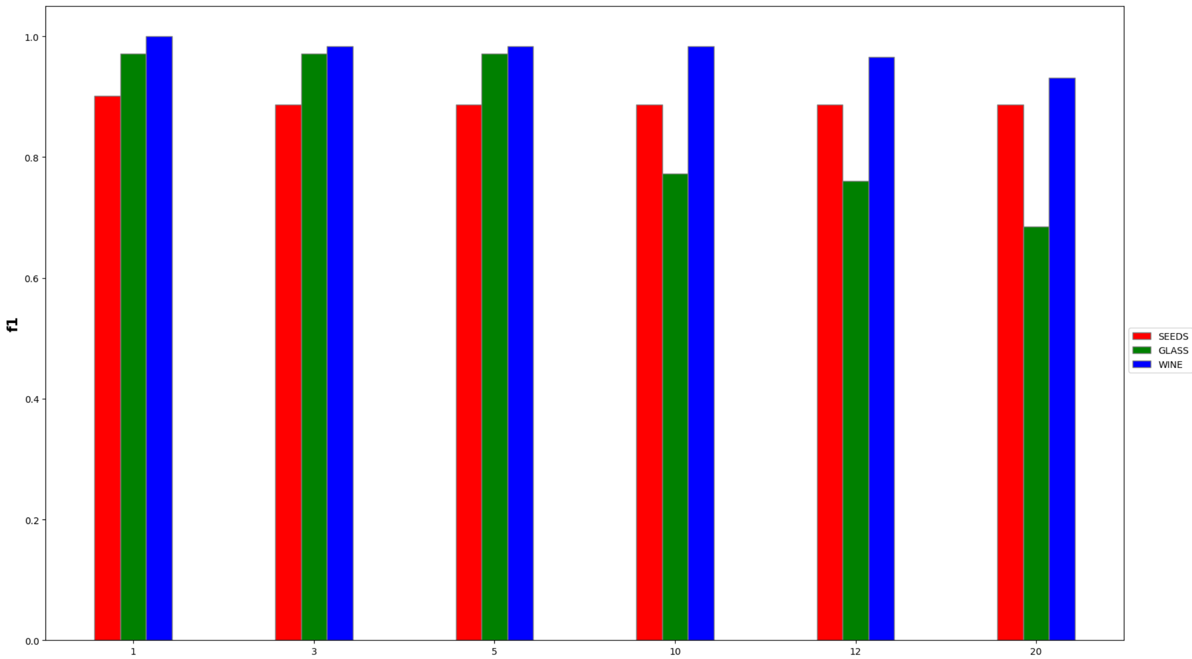

```
In [ ]: combineFigsInOnePlot(results_list[2], dataset_list[2])
```



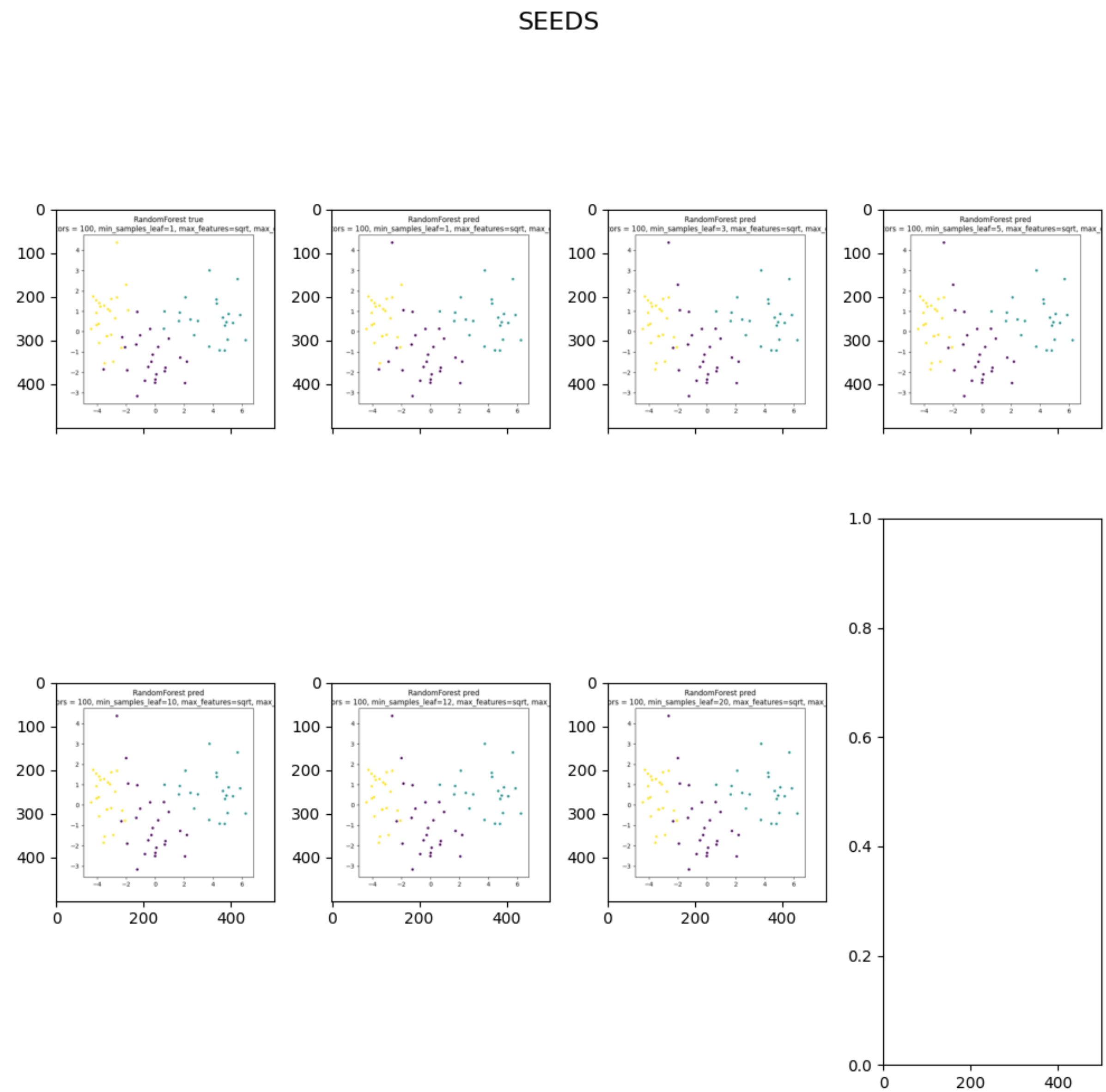
Random forest - liczba samplow

In [ ]:
```
study_vals = [1, 3, 5, 10, 12, 20]
results_list = [
[run_random_forest (df_seeds, min_samples_leaf = c) for c in study_vals],
[run_random_forest (df_glass, min_samples_leaf = c) for c in study_vals],
[run_random_forest (df_wine, min_samples_leaf = c) for c in study_vals],
]
```

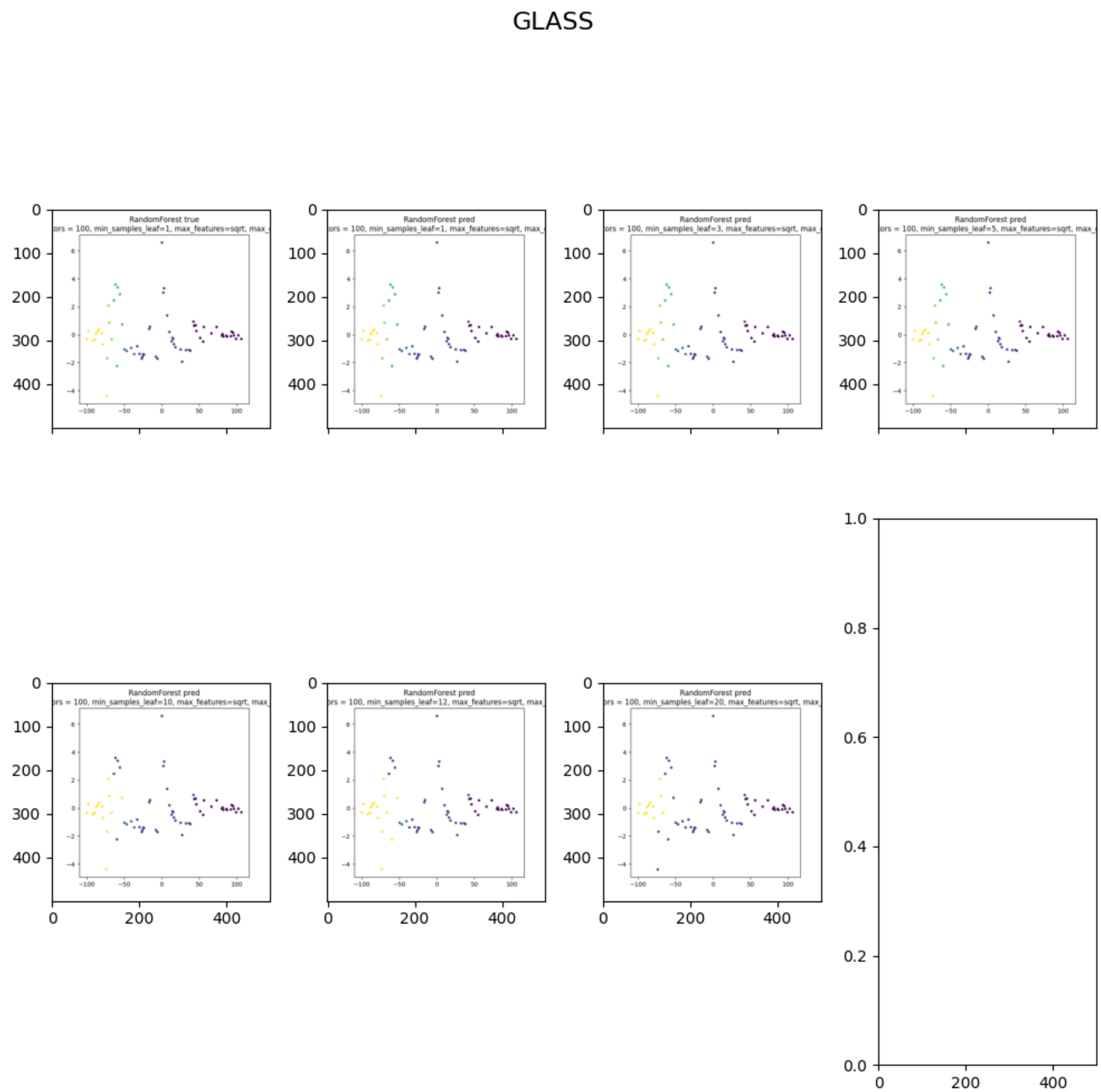
In [ ]:
```
plotStatistics(results_list, metrics_list, study_vals, dataset_list, colour_list)
```



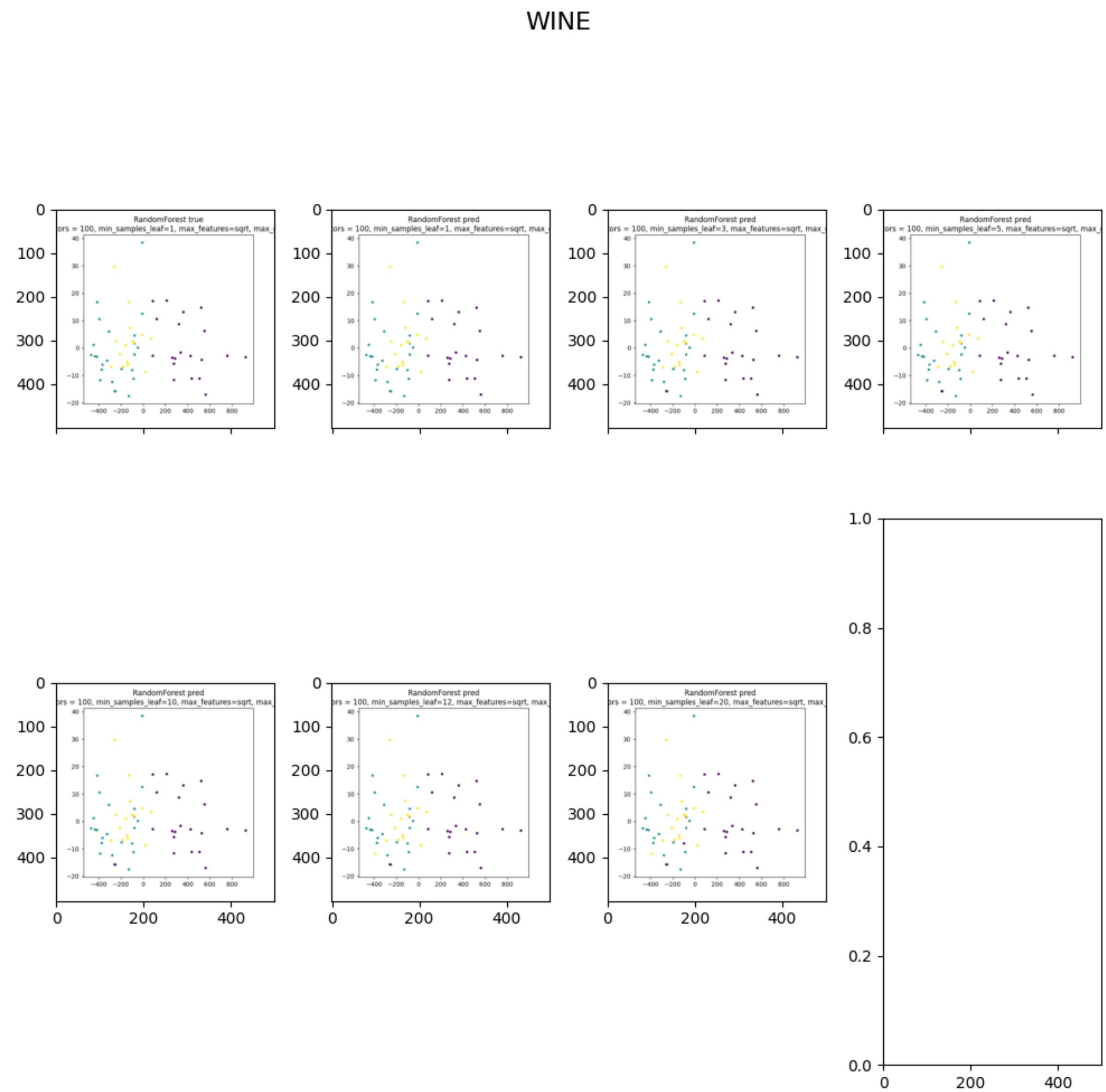
In [ ]:
```
combineFigsInOnePlot(results_list[0], dataset_list[0])
```




```
In [ ]: combineFigsInOnePlot(results_list[1], dataset_list[1])
```



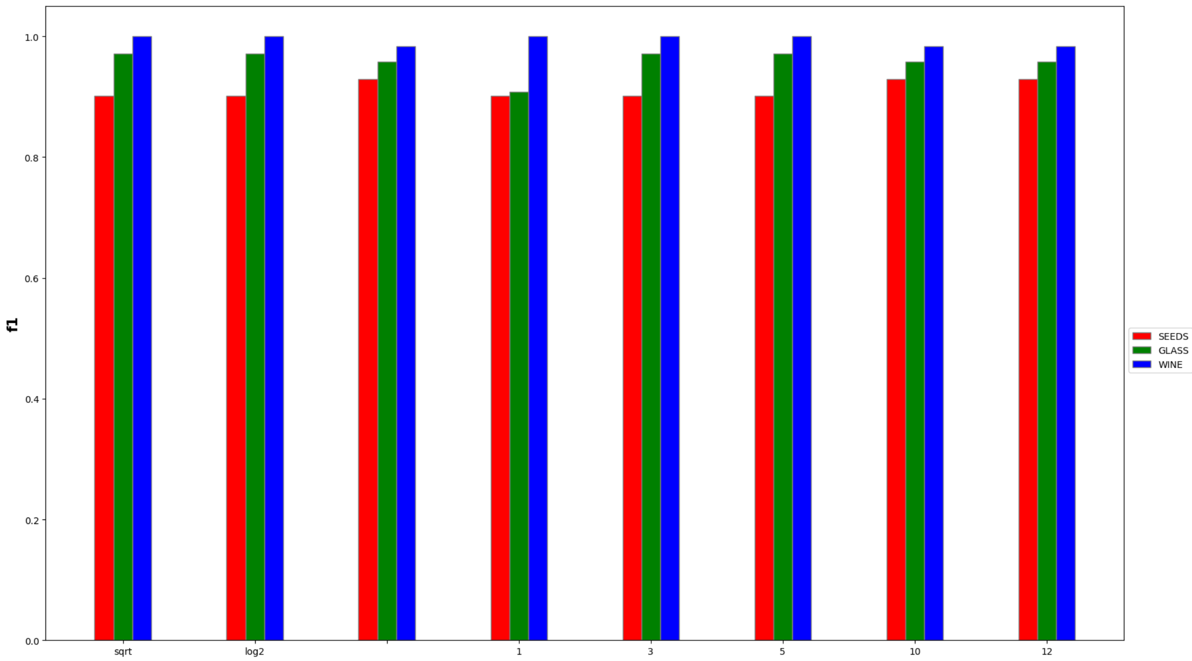

```
In [ ]: combineFigsInOnePlot(results_list[2], dataset_list[2])
```



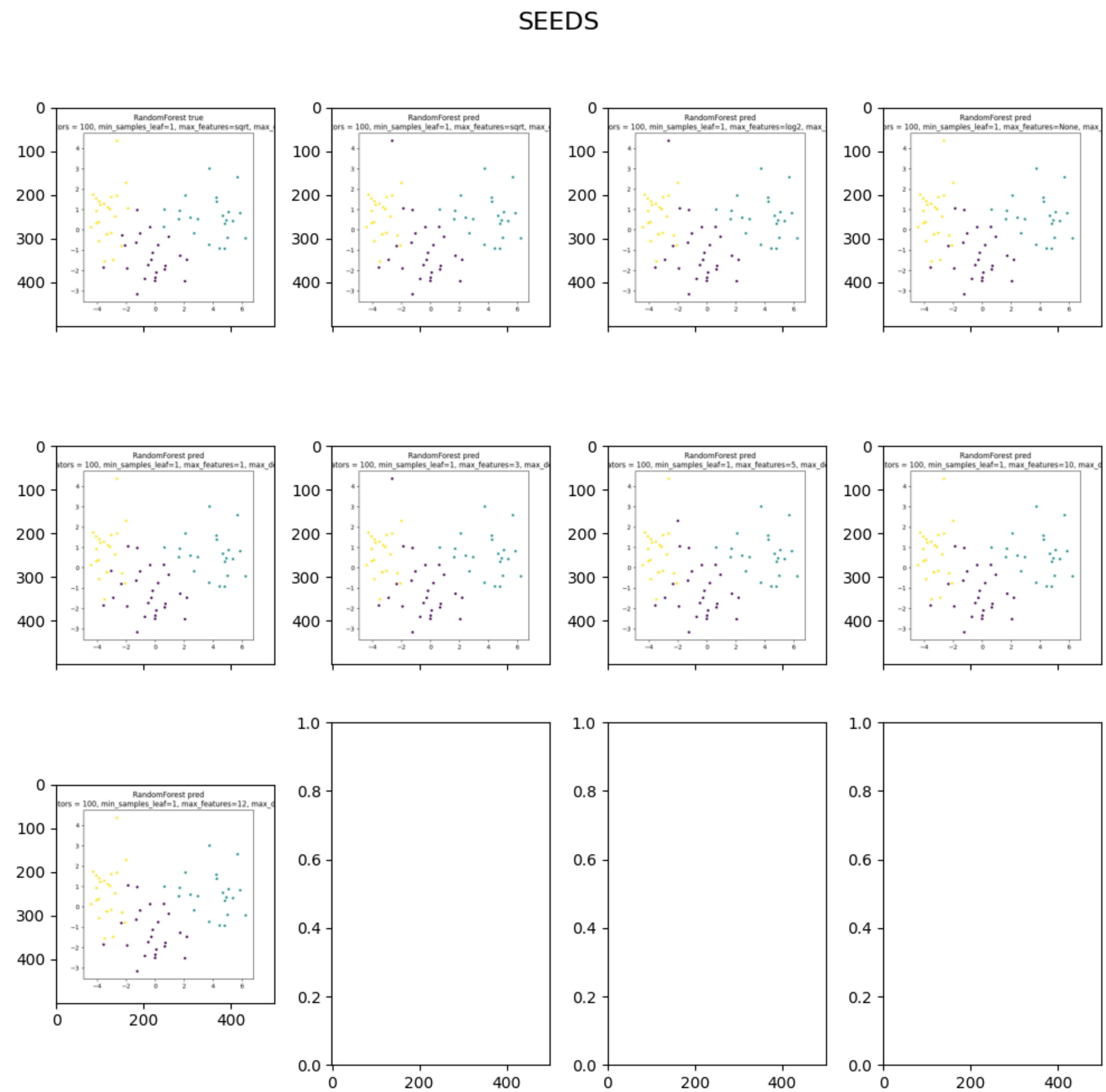
Random forest - liczba cech

In [ ]:
```
study_vals = ['sqrt', 'log2', None, 1, 3, 5, 10, 12]
results_list = [
[run_random_forest (df_seeds, max_features = c) for c in study_vals],
[run_random_forest (df_glass, max_features = c) for c in study_vals],
[run_random_forest (df_wine, max_features = c) for c in study_vals],
]
```

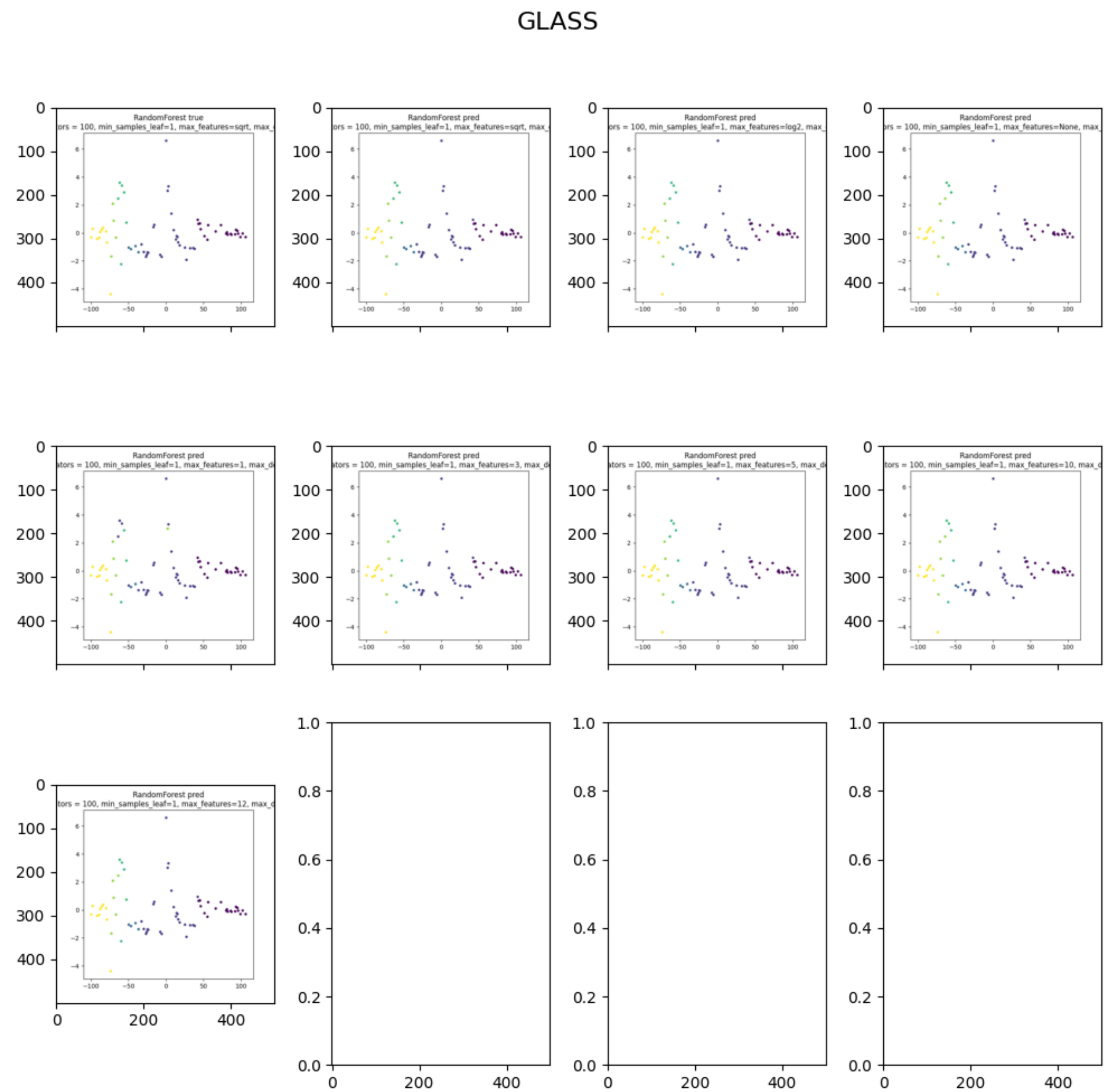
In [ ]:
```
plotStatistics(results_list, metrics_list, study_vals, dataset_list, colour_list)
```



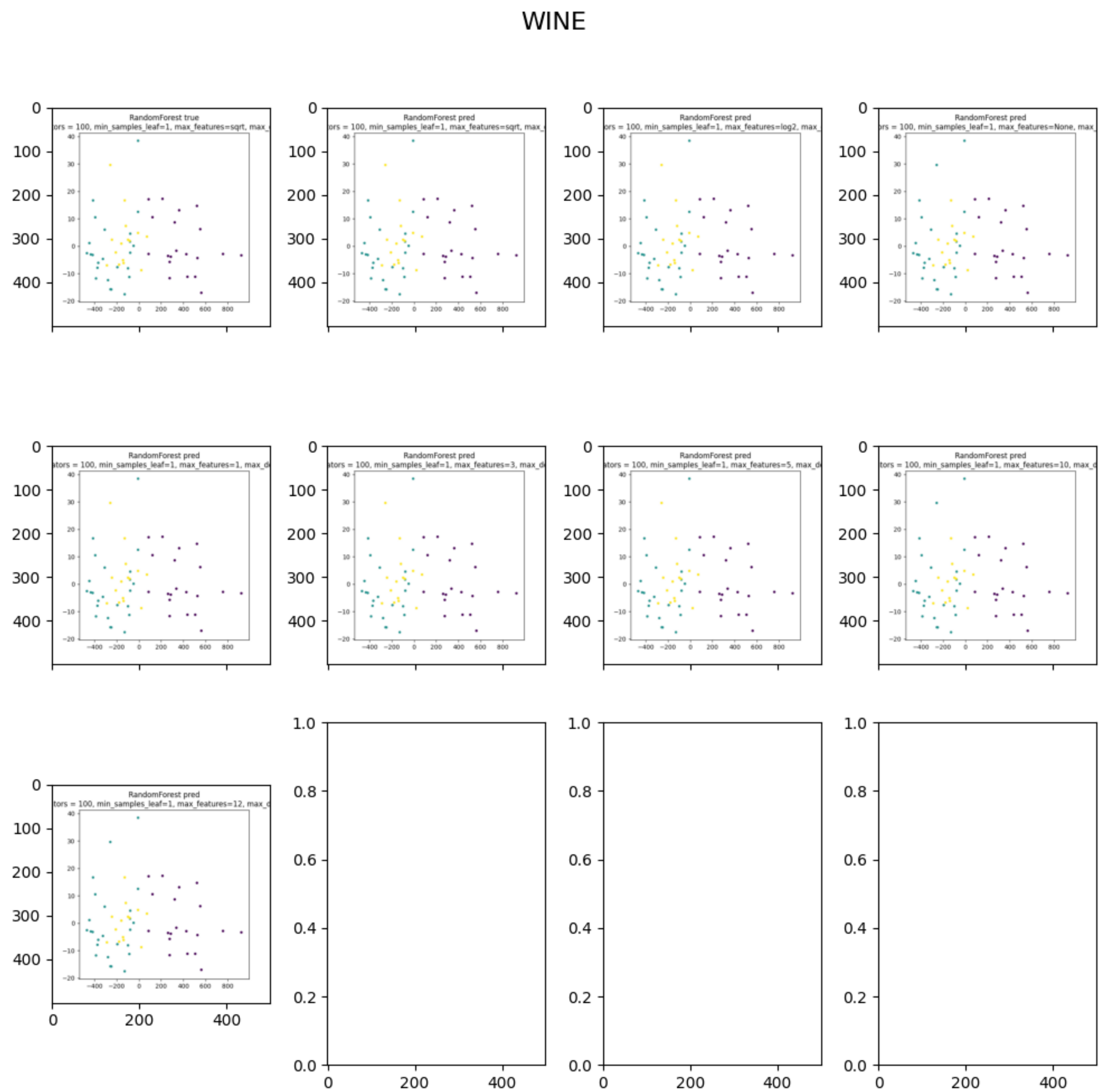
In [ ]:
```
combineFigsInOnePlot(results_list[0], dataset_list[0])
```



In [ ]:
```python
combineFigsInOnePlot(results_list[1], dataset_list[1])
```



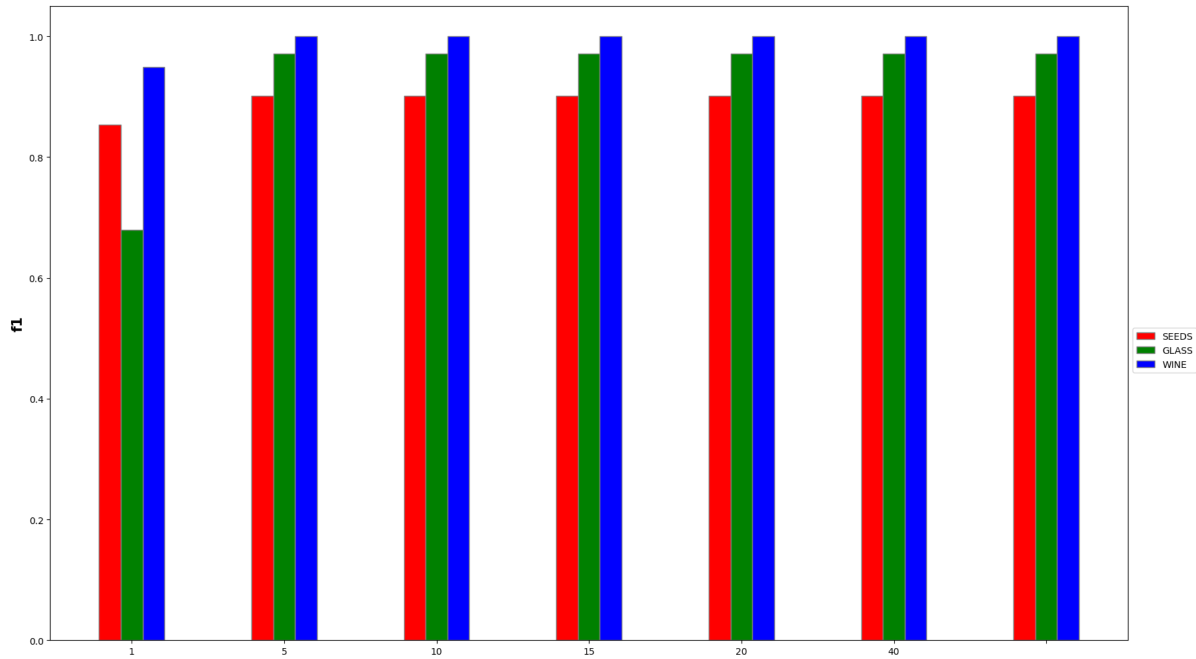
In [ ]:
```
combineFigsInOnePlot(results_list[2], dataset_list[2])
```



Random forest - glebokosc

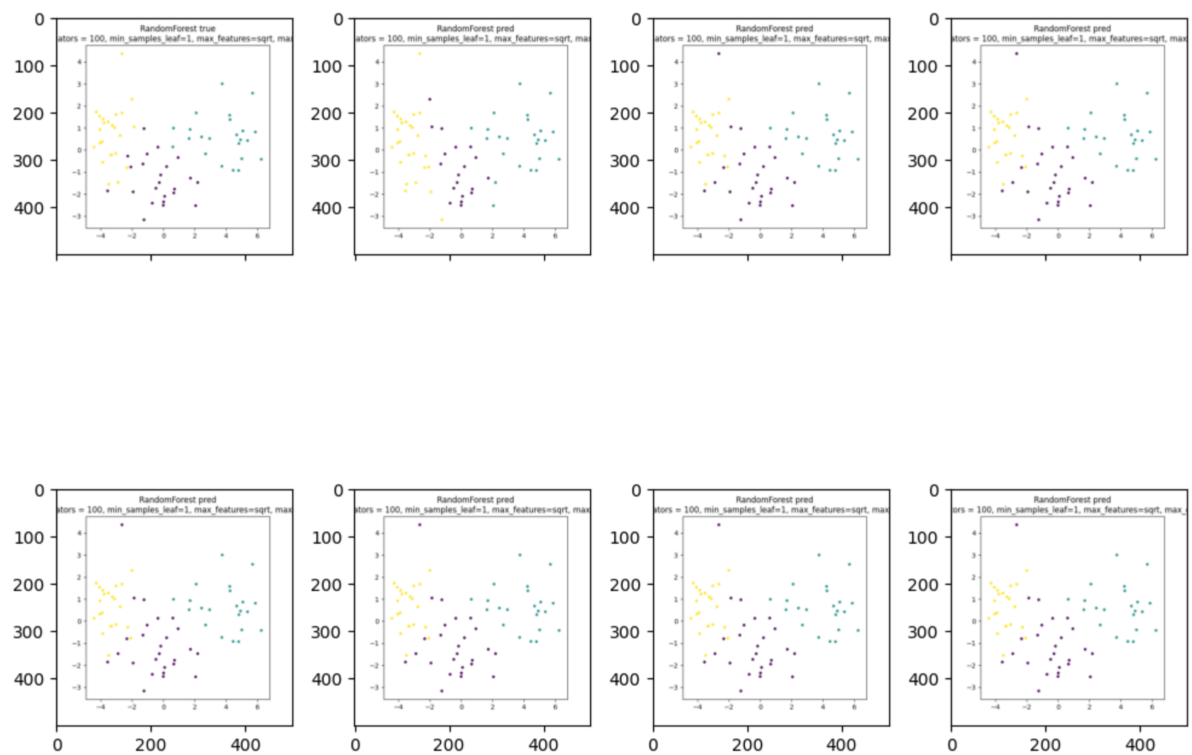
In [ ]:
```
study_vals = [ 1, 5, 10, 15, 20, 40, None]
results_list = [
[run_random_forest (df_seeds, max_depth = c) for c in study_vals],
[run_random_forest (df_glass, max_depth = c) for c in study_vals],
[run_random_forest (df_wine, max_depth = c) for c in study_vals],
]
```

In [ ]:
```
plotStatistics(results_list, metrics_list, study_vals, dataset_list, colour_list)
```

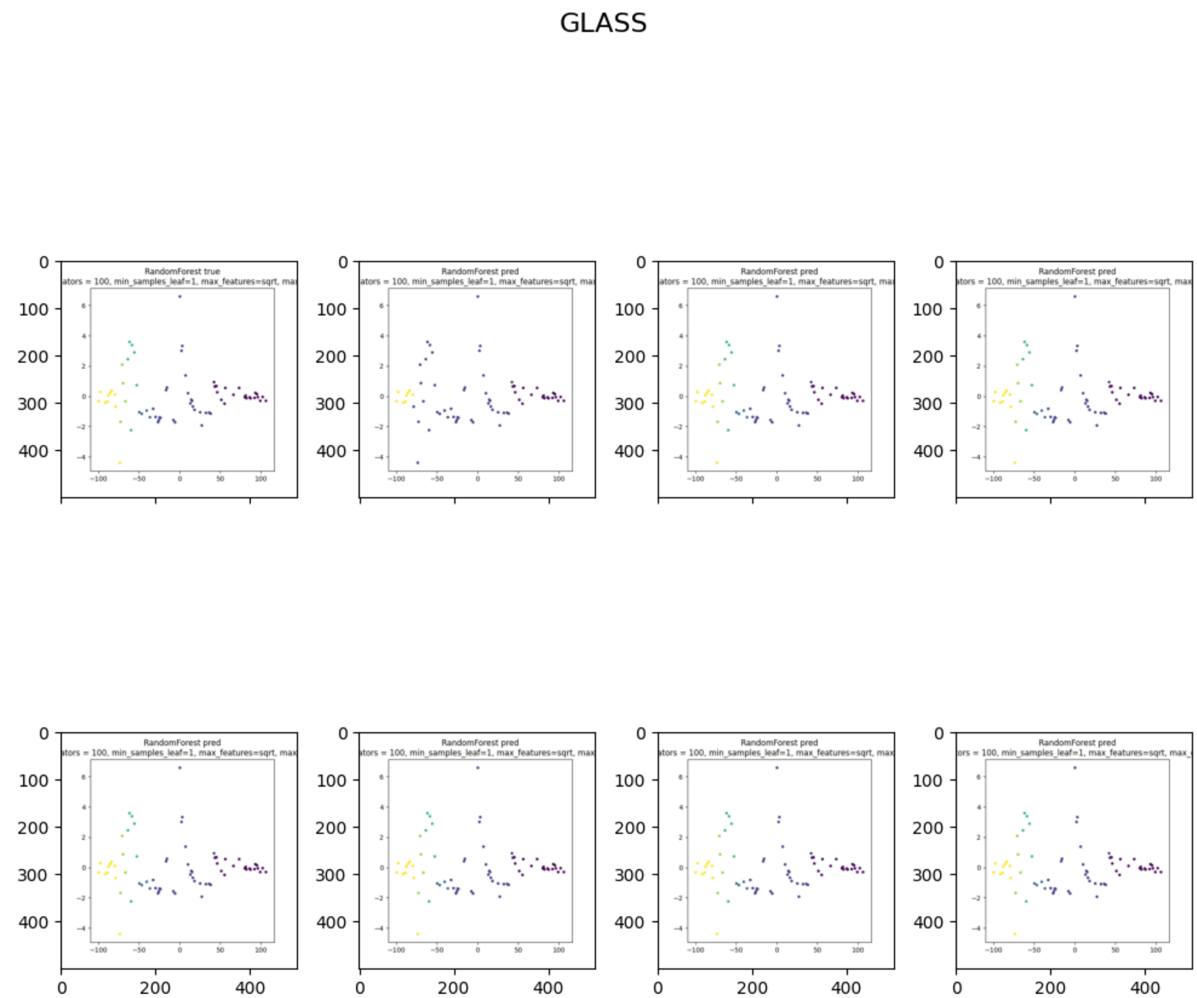



```
In [ ]: combineFigsInOnePlot(results_list[0], dataset_list[0])
```

SEEDS

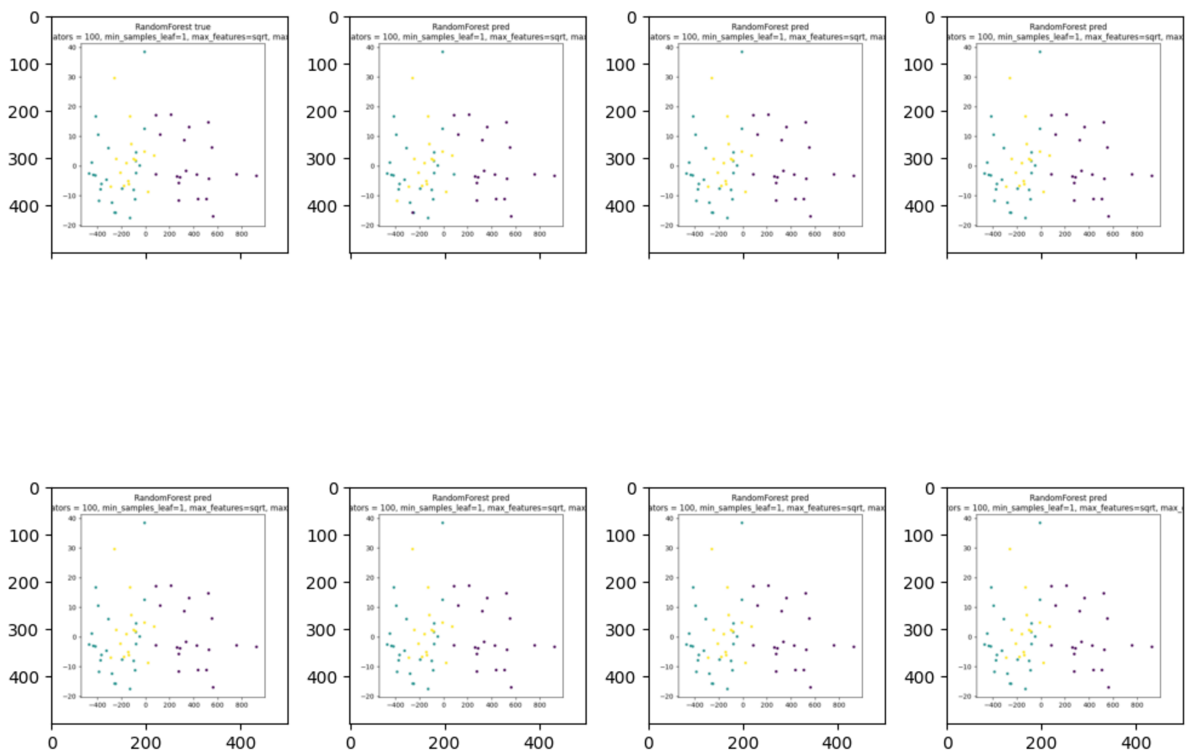



```
In [ ]: combineFigsInOnePlot(results_list[1], dataset_list[1])
```



In [ ]:
```
combineFigsInOnePlot(results_list[2], dataset_list[2])
```

WINE



In [ ]:
```
score_metric = 'f1'
results_df = pd.DataFrame([
[RunKNN (df_iris)[score_metric], run_bagging (df_iris)[score_metric], run_adaboost
[RunKNN (df_seeds)[score_metric], run_bagging (df_seeds)[score_metric], run_adaboos
[RunKNN (df_glass)[score_metric], run_bagging (df_glass)[score_metric], run_adaboos
[RunKNN (df_wine)[score_metric], run_bagging (df_wine)[score_metric], run_adaboost
], index=['IRIS', 'SEEDS', 'GLASS', 'WINE'], columns = ['f1 KNN', 'f1 bagging', 'f1

results_df
```

```
              precision    recall  f1-score   support

           0       1.00      1.00      1.00        19
           1       0.94      1.00      0.97        15
           2       1.00      0.94      0.97        16

    accuracy                           0.98        50
   macro avg       0.98      0.98      0.98        50
weighted avg       0.98      0.98      0.98        50

Cross val:  0.9666666666666667
              precision    recall  f1-score   support

           1       0.80      0.87      0.83        23
           2       1.00      0.91      0.95        23
           3       0.88      0.88      0.88        24

    accuracy                           0.89        70
   macro avg       0.89      0.89      0.89        70
weighted avg       0.89      0.89      0.89        70

Cross val:  0.9047619047619048
              precision    recall  f1-score   support

           1       1.00      0.91      0.95        22
           2       0.93      1.00      0.96        25
           3       1.00      1.00      1.00         4
           5       1.00      0.83      0.91         6
           6       0.80      1.00      0.89         4
           7       1.00      1.00      1.00        10

    accuracy                           0.96        71
   macro avg       0.95      0.96      0.95        71
weighted avg       0.96      0.96      0.96        71

Cross val:  0.9767214397496088
              precision    recall  f1-score   support

           0       0.85      0.85      0.85        20
           1       0.67      0.67      0.67        24
           2       0.47      0.47      0.47        15

    accuracy                           0.68        59
   macro avg       0.66      0.66      0.66        59
weighted avg       0.68      0.68      0.68        59

Cross val:  0.6402071563088512
```

Out[ ]:

	f1 KNN	f1 bagging	f1 boost	f1 forest
IRIS	0.980000	1.000000	0.878487	0.980000
SEEDS	0.885714	0.887773	0.498168	0.901039
GLASS	0.957746	0.971702	0.702701	0.971702
WINE	0.677966	0.966270	0.895931	1.000000

In [ ]: