In [1]:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.base import clone
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.discriminant_analysis import LinearDiscriminantAnalysis, QuadraticD
from sklearn.neighbors import KNeighborsClassifier
from sklearn.naive_bayes import GaussianNB
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier, AdaBoostClassifier, Gradien
from sklearn.neural_network import MLPClassifier
from sklearn.gaussian_process import GaussianProcessClassifier
from xgboost import XGBClassifier
from sklearn.gaussian_process.kernels import RBF
from sklearn.svm import SVC
from sklearn.metrics import classification_report
from sklearn.metrics import confusion_matrix
from sklearn.metrics import accuracy_score
from sklearn.pipeline import Pipeline
from sklearn.model_selection import RepeatedStratifiedKFold
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import GridSearchCV
from sklearn.feature_selection import RFECV
from sklearn.preprocessing import LabelEncoder

import warnings
warnings.filterwarnings('ignore')

le = LabelEncoder()
```

Pulling in our dataset

Here we have our dataset of historic NBA Draft Prospect data. The data consists of stats from their whole college career as well as a label of their role in their careers in the NBA. College stats are scraped from Sports Reference CBB.

Labels

The labels for this dataset indicate whether a player is a "Star", "Starter", "Role" Player, or "Non-NBA. These labels are calculated by a combination of their Points/Game, Minutes Played/Game, and Basketball Reference's VORP (Value over Replacement Player) statistic. Definitions of each label are below.

Star

Player has averaged over 14 Points/Game, 28 Mins/Game, and 0.017 over the course of their career.

Starter

Player has averaged over 25 Mins/Game

Role

Player has averaged between 10 and 25 Mins/Game

Non-NBA

Player has averaged less than 10 Mins/Game

The definitions of these labels come from the "Pareto Principle" which states that "80% of consequences come from 20% of the causes". In NBA terms, that means 20% of players in the NBA contribute to 80% of winning contributions. I use percentiles of VORP, Points, and Minutes to determine the parameters of these label definitions

In [2]:

```
base_data = pd.read_csv('./datasets/AllProspects.csv')
base_data['Label'] = le.fit_transform(base_data['Label'])
```

In [3]:

```
data = base_data.copy()
data.drop('School', axis=1, inplace=True)
data.drop('Player', axis=1, inplace=True)
```

We drop the "School" label in our Dataset. Without it, our inputs will be strictly quantatative and easier to handle. Plus, it is somewhat redundant with SOS (strength of schedule) as both indicate the size of competition encountered during college.

In [4]:

```
def accurate_confidence_score(predict, actual, classes):
    sum_correct = 0
    for i in range(len(predict)):
        index = np.where(classes == actual.iat[i])
        sum_correct += predict[i][index]
    return sum_correct/len(predict)

def predict(plainmodel, data):
    data_with_meta = data.reindex(np.random.permutation(data.index))
    data = data_with_meta.copy()
    data.drop('School', axis=1, inplace=True)
    data.drop('Player', axis=1, inplace=True)
    final_df = pd.concat([pd.DataFrame().reindex_like(data_with_meta), pd.DataFr
    for i in range(1990,2022):
        model = clone(plainmodel)
        export = data_with_meta[data_with_meta['Year'] == i]
        train = data[data['Year'] != i]
        test = data[data['Year'] == i]
#         train.drop('Year', axis=1, inplace=True)
#         test.drop('Year', axis=1, inplace=True)
        X_train = train.loc[:, train.columns != 'Label']
        y_train = train['Label']
        X_test = test.loc[:, test.columns != 'Label']
        y_test = test['Label']
```

```
        model.fit(X_train, y_train)
        final_prediction = model.predict_proba(X_test)

        NBAe = []
        Startere = []
        Stare = []
        for i in range(len(final_prediction)):
            row = final_prediction[i]
            NBAe.append(row[1] + row[2] + row[3])
            Startere.append(row[2] + row[3])
            Stare.append(row[2])

        export['NBA%'] = NBAe
        export['Starter%'] = Startere
        export['Star%'] = Stare
        final_df = pd.concat([final_df, export], ignore_index=True)
    return final_df

def eval(plainmodel,data):
    acc_scores = []
    conf_matrix = np.zeros(shape=(4,4), dtype=float)
    labels=[0,1,3,2]
    graph_labels=['Non-NBA', 'Role', 'Starter', 'Star']
    acs = []
    opt = []
    opt_len = 0
    for i in range(1990,2022):
        model = clone(plainmodel)
        data = data.reindex(np.random.permutation(data.index))
        train = data[data['Year'] != i]
        test = data[data['Year'] == i]
#         train.drop('Year', axis=1, inplace=True)
#         test.drop('Year', axis=1, inplace=True)
        X_train = train.loc[:, train.columns != 'Label']
        y_train = train['Label']
        X_test = test.loc[:, test.columns != 'Label']
        y_test = test['Label']
        model.fit(X_train, y_train)
        predict = model.predict(X_test)
        for i in range(len(predict)):
            opt.append(labels.index(predict[0]) - labels.index(y_test.iat[0]))
        predictC = model.predict_proba(X_test)
        acc_scores.append(accuracy_score(predict, y_test))
        conf_matrix += confusion_matrix(y_test, predict, labels=labels)
        acs.append(accurate_confidence_score(predictC, y_test, model.classes_))

    print("Accuracy:", sum(acc_scores)/len(acc_scores))
    fig = plt.figure()
    ax = fig.add_subplot(111)
    cax = ax.matshow(conf_matrix)
    plt.title('Confusion matrix of the classifier')
    fig.colorbar(cax)
    ax.set_xticklabels([''] + graph_labels)
    ax.set_yticklabels([''] + graph_labels)
    plt.xlabel('Predicted')
    plt.ylabel('True')
    plt.show()
    print("ACS:", sum(acs)/len(acs))
    print("Optimism:", sum(opt)/len(opt))
    print()
```

```
def tune(plainmodel, param_space, basic_data):
    model = clone(plainmodel)
    data = basic_data.copy()
#     data.drop('Year', axis=1, inplace=True)
    X = data.loc[:, data.columns != 'Label']
    y = data['Label']
    clf = GridSearchCV(model, param_space, cv=15)
    clf.fit(X, y)
    print('Best parameters found:\n', clf.best_params_)
    return clf.best_estimator_
```

Here we test a bunch of models offered to us by sklearn

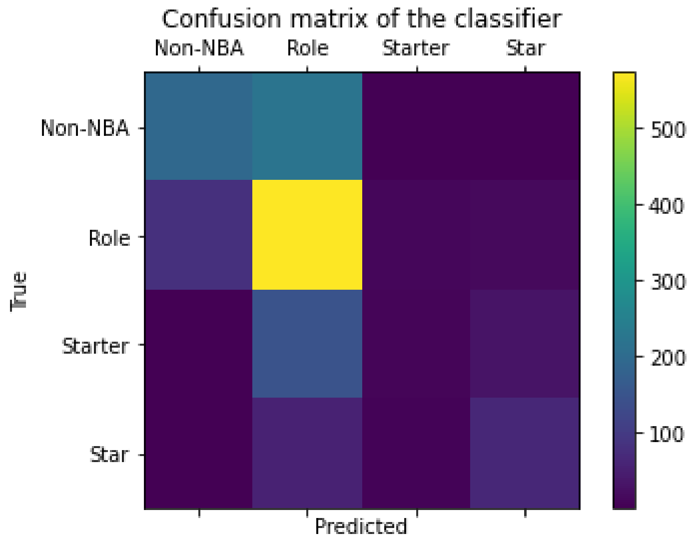
In [5]:

```
logreg_model =  LogisticRegression()
Nb_model = GaussianNB()
LDA_model = LinearDiscriminantAnalysis()
QDA_model = QuadraticDiscriminantAnalysis()
KNN_model = KNeighborsClassifier()
Dtree_model = DecisionTreeClassifier()
Rf_model = RandomForestClassifier()
Ada_model = AdaBoostClassifier()
XGB_model = XGBClassifier(objective='multi:softproba',nthread=6,seed=42,verbosit
MLP_model = MLPClassifier()
models = [(XGB_model,{'max_depth': range (2, 10, 1),'booster':['gbtree', 'gbline
          (Nb_model, {'var_smoothing': np.logspace(0,-9, num=100)}),
          (LDA_model, {'solver': ['svd', 'lsqr', 'eigen'], 'n_components': list(
          (QDA_model, {'reg_param': [0.1, 0.2, 0.3, 0.4, 0.5], 'store_covariance
          (logreg_model, {"C":np.logspace(-3,3,7), "penalty":["l1","l2"]}),
          (KNN_model, dict(n_neighbors=list(range(1, 31)))),
          (Dtree_model, {'criterion':['gini','entropy'],'max_depth':[4,5,6,7,8,9
          (Rf_model, { 'n_estimators': [100, 200, 500],'max_features': ['auto',
          (Ada_model,{'base_estimator': [Nb_model, LDA_model, QDA_model, KNN_mod
          (MLP_model, {'hidden_layer_sizes': [(50,50,50), (50,100,50), (100,)],'
         ]
```

In [6]:

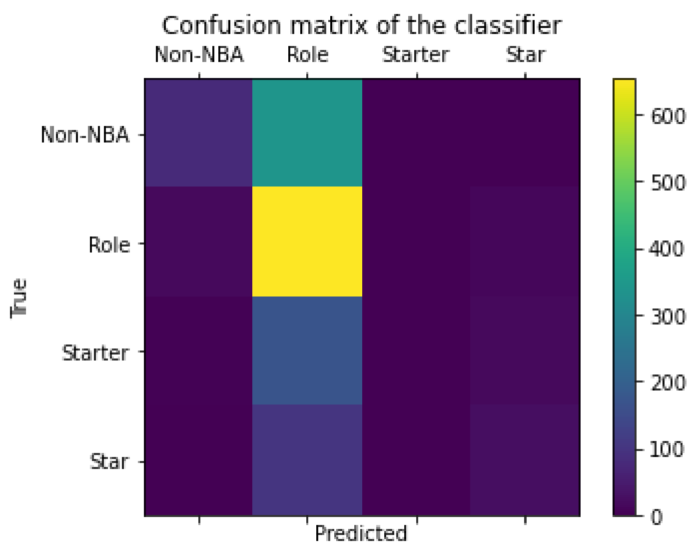
```
filtered_data = data
for item in models:
    model = item[0]
    params = item[1]
    print(type(model))
    best_model = tune(model, params, filtered_data)
    eval(best_model, filtered_data)
    print()
```

```
<class 'xgboost.sklearn.XGBClassifier'>
Best parameters found:
 {'booster': 'gbtree', 'learning_rate': 0.01, 'max_depth': 2, 'n_estimators': 18
0}
Accuracy: 0.5929188451519046
```



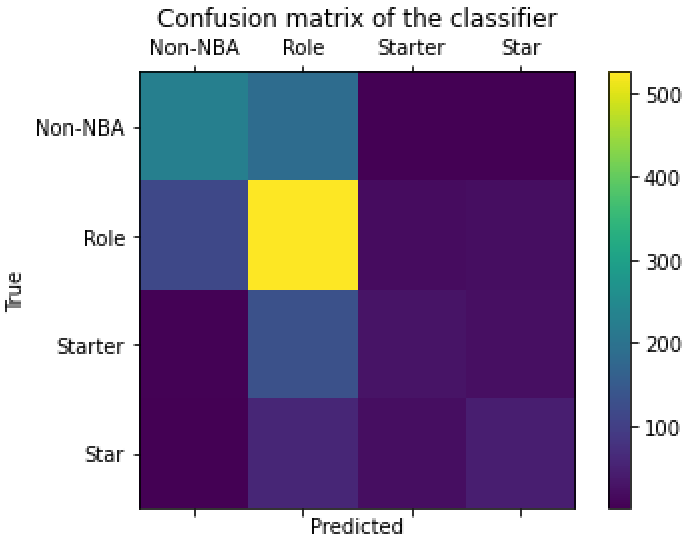

```
ACS: [0.3924071]
Optimism: -0.023255813953488372


<class 'sklearn.naive_bayes.GaussianNB'>
Best parameters found:
 {'var_smoothing': 0.0657933224657568}
Accuracy: 0.5284972264530238
```



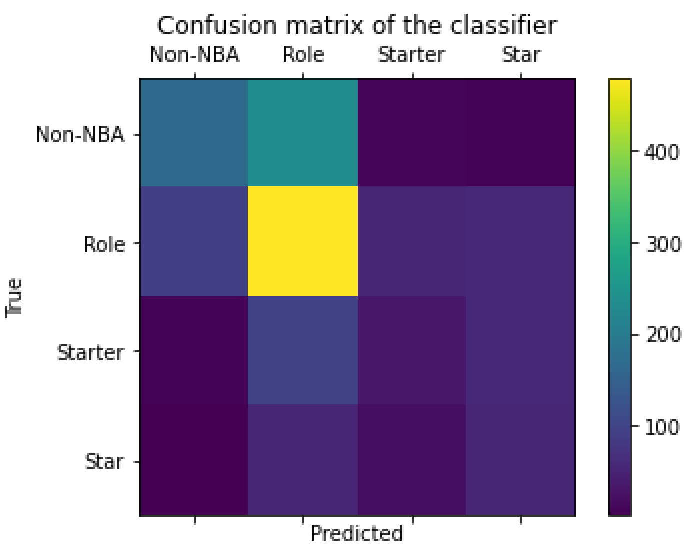

```
ACS: [0.43906695]
Optimism: 0.03453136011275546


<class 'sklearn.discriminant_analysis.LinearDiscriminantAnalysis'>
Best parameters found:
 {'n_components': 0, 'shrinkage': 'auto', 'solver': 'lsqr', 'store_covariance':
True}
Accuracy: 0.5841383946949731
```



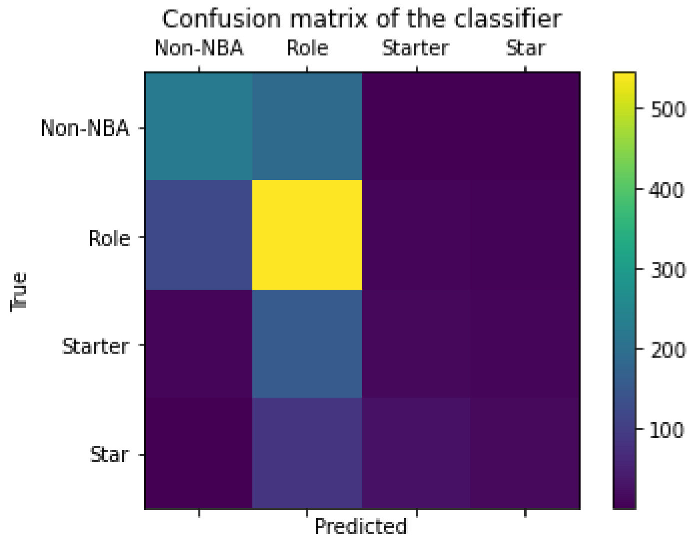

```
ACS: [0.4667075]
Optimism: 0.09372797744890768


<class 'sklearn.discriminant_analysis.QuadraticDiscriminantAnalysis'>
Best parameters found:
 {'reg_param': 0.4, 'store_covariance': True, 'tol': 0.0001}
Accuracy: 0.5147777695488415
```



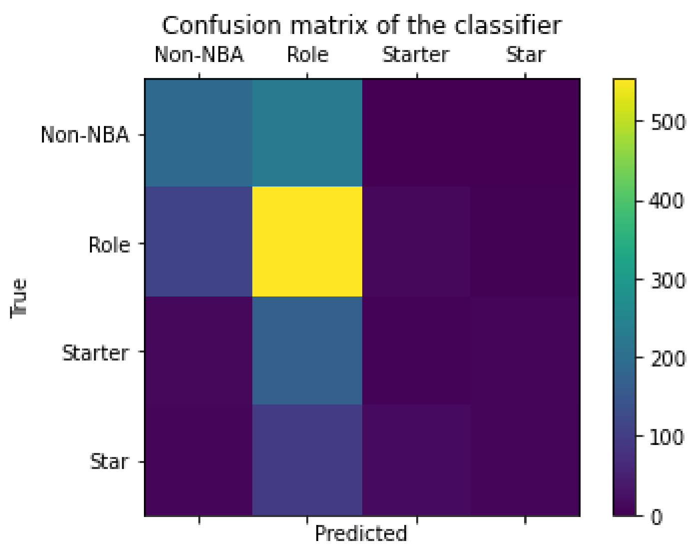

```
ACS: [0.47605838]
Optimism: 0.2727272727272727


<class 'sklearn.linear_model._logistic.LogisticRegression'>
Best parameters found:
 {'C': 0.01, 'penalty': 'l2'}
Accuracy: 0.5618135429857568
```



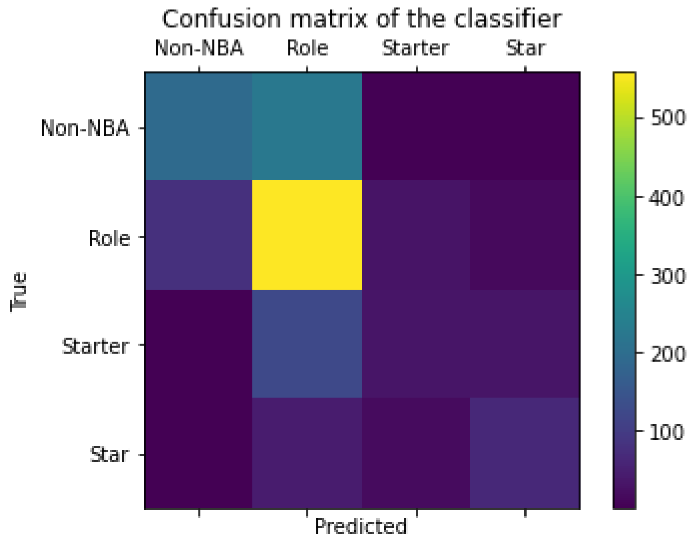

```
ACS: [0.4493354]
Optimism: -0.18957011980267793


<class 'sklearn.neighbors._classification.KNeighborsClassifier'>
Best parameters found:
 {'n_neighbors': 20}
Accuracy: 0.5287649792301126
```



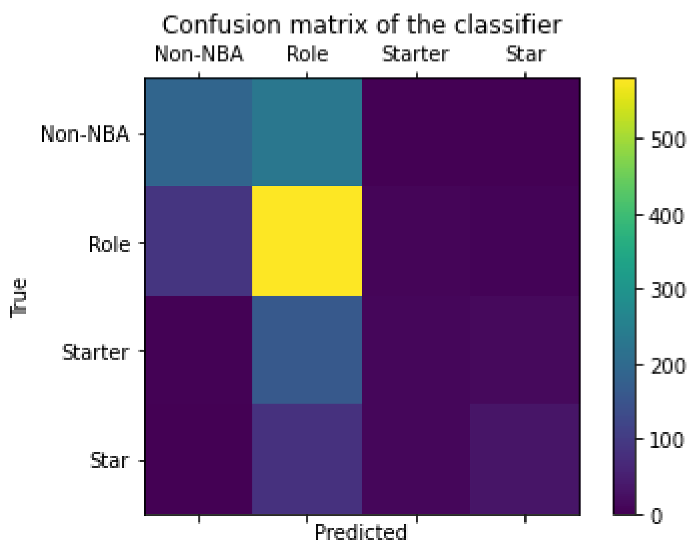

```
ACS: [0.43240906]
Optimism: -0.10359408033826638


<class 'sklearn.tree._classes.DecisionTreeClassifier'>
Best parameters found:
 {'criterion': 'entropy', 'max_depth': 4}
Accuracy: 0.5978806129371385
```



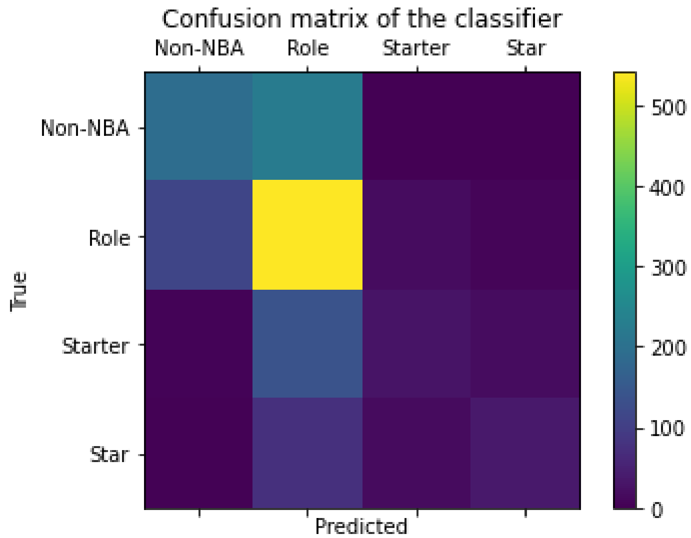

```
ACS: [0.46641477]
Optimism: -0.019732205778717406
```

```
<class 'sklearn.ensemble._forest.RandomForestClassifier'>
Best parameters found:
 {'criterion': 'gini', 'max_depth': 8, 'max_features': 'auto', 'n_estimators': 1
00}
Accuracy: 0.5693254058593846
```



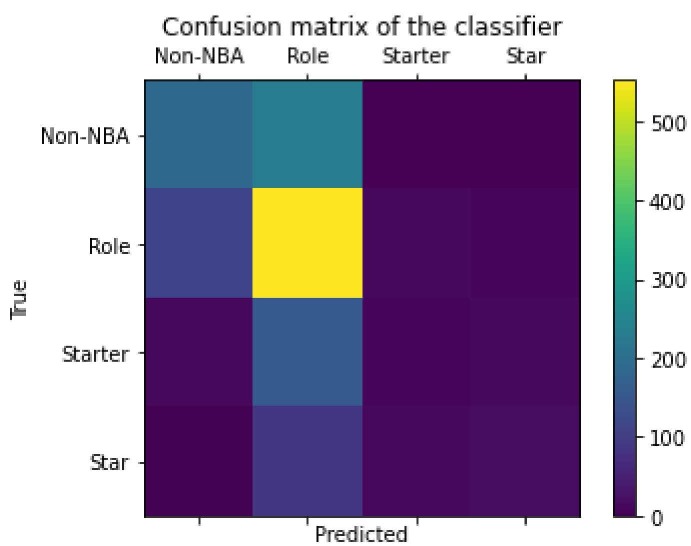

```
ACS: [0.42543855]
Optimism: -0.22692036645525018
```

```
<class 'sklearn.ensemble._weight_boosting.AdaBoostClassifier'>
Best parameters found:
 {'algorithm': 'SAMME.R', 'base_estimator': RandomForestClassifier(), 'learning_
rate': 1.01, 'n_estimators': 20}
Accuracy: 0.5603856355738501
```




```
ACS: [0.43104276]
Optimism: -0.1945031712473573
```

```
<class 'sklearn.neural_network._multilayer_perceptron.MLPClassifier'>
Best parameters found:
 {'activation': 'tanh', 'alpha': 0.05, 'hidden_layer_sizes': (100,), 'learning_r
ate': 'adaptive', 'solver': 'adam'}
Accuracy: 0.5382040801705688
```




```
ACS: [0.43391543]
Optimism: -0.10923185341789993
```

Accurate Confidence Score

Accurate Confidence Score is a metric I have created that measures the average confidence a model has in predicting the actual label of the dataset. In mathematical terms:

ACS = sum(predict_probability[correct label])/ len(dataset)

In [10]:

```
final_data = base_data.copy()
model = XGBClassifier(objective='multi:softproba',nthread=6,seed=42,verbosity =
predict_data = predict(model, final_data)
names = predict_data.pop('Player')
pick = predict_data.pop('Pick')
year = predict_data.pop('Year')
label = predict_data.pop('Label')
predict_data.insert(0, 'Player', names)
predict_data.insert(1, 'Pick', year)
predict_data.insert(2, 'Year', year)
predict_data.insert(3, 'Label', label)
predict_data = predict_data.sort_values(by=['Star%'], ascending=False)
predict_data = predict_data.sort_values(by=['Year'], ascending=False, kind='stab
predict_data.to_csv('./result/Predicted.csv',index=False)
```

In [11]:

```
train_data = base_data.copy()
train_data.drop('School', axis=1, inplace=True)
train_data.drop('Player', axis=1, inplace=True)
X_train = train_data.loc[:, train_data.columns != 'Label']
y_train = train_data['Label']
predict_data = pd.read_csv('./datasets/2022Prospects.csv')
predict_data = predict_data.fillna(0)
predict_data = predict_data.reindex(np.random.permutation(predict_data.index))
names = predict_data.pop('Player')
school = predict_data.pop('School')

model = XGBClassifier(objective='multi:softproba',nthread=6,seed=42,verbosity =
model.fit(X_train, y_train)
final_prediction = model.predict_proba(predict_data)

NBAe = []
Startere = []
Stare = []

for i in range(len(final_prediction)):
        row = final_prediction[i]
        NBAe.append(row[1] + row[2] + row[3])
        Startere.append(row[2] + row[3])
        Stare.append(row[2])

predict_data['School'] = school
predict_data['NBA%'] = NBAe
predict_data['Starter%'] = Startere
predict_data['Star%'] = Stare
year = predict_data.pop('Year')
pick =  predict_data.pop('Pick')
predict_data.insert(0, 'Player', names)
predict_data.insert(1, 'Pick', pick)
predict_data.insert(2, 'Year', year)
predict_data = predict_data.sort_values(by=['Star%'], ascending=False)
predict_data.to_csv('./result/2022Predicted.csv',index=False)
```

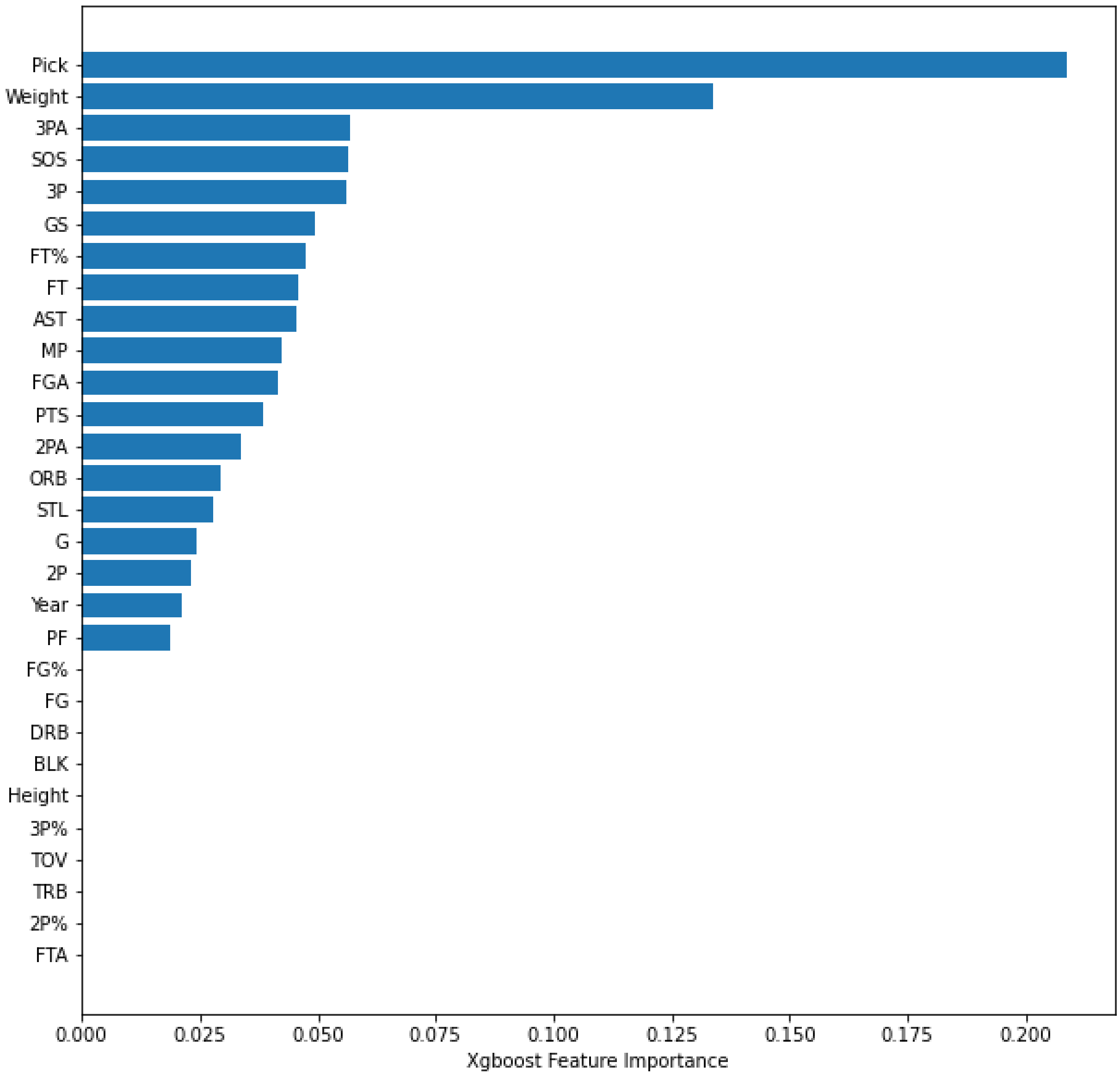
Feature selection

In [12]:

```
train_data = base_data.copy()
train_data.drop('School', axis=1, inplace=True)
```

```python
train_data.drop('Player', axis=1, inplace=True)
# train_data.drop('Year', axis=1, inplace=True)
X_train = train_data.loc[:, train_data.columns != 'Label']
y_train = train_data['Label']

xgb_model = XGBClassifier(objective='multi:softproba',nthread=6,seed=42,verbosit
xgb_model.fit(X_train,y_train)
sorted_idx = xgb_model.feature_importances_.argsort()
plt.figure(figsize=(10, 10))
plt.barh(X_train.columns[sorted_idx], xgb_model.feature_importances_[sorted_idx]
plt.xlabel("Xgboost Feature Importance")
plt.show()
```



In [13]:

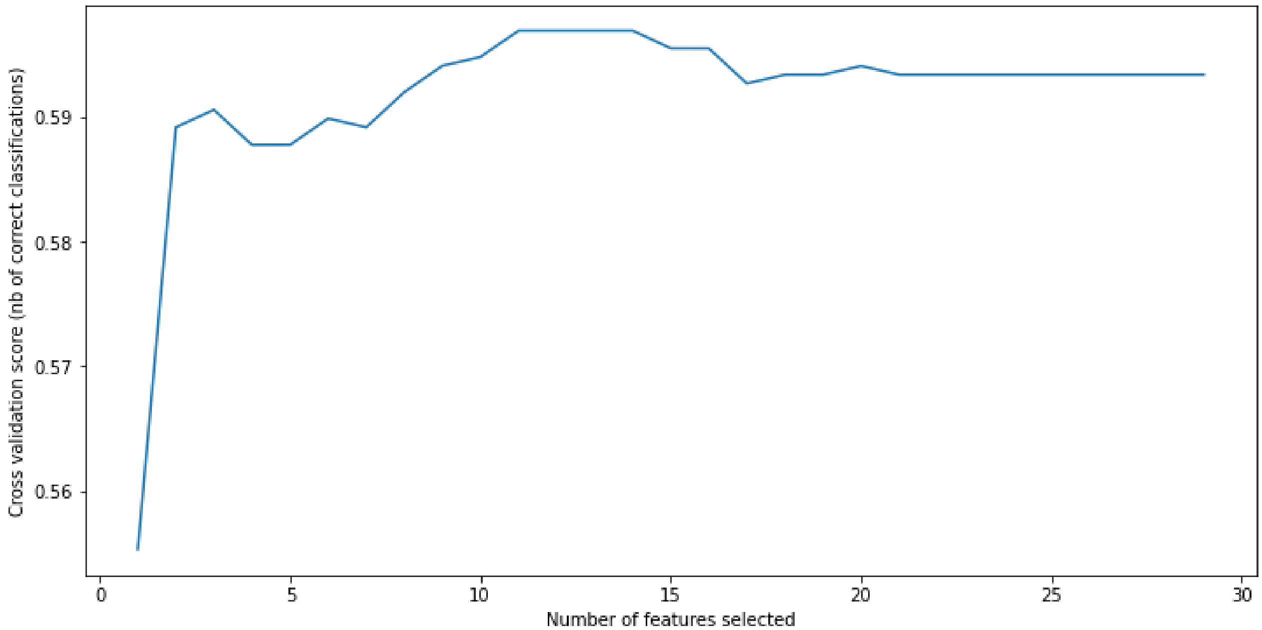
```python
rfecv = RFECV(estimator=XGBClassifier(objective='multi:softproba',nthread=6,seed
model = XGBClassifier(objective='multi:softproba',nthread=6,seed=42,verbosity =
pipeline = Pipeline([('Feature Selection', rfecv), ('Model', model)])
cv = RepeatedStratifiedKFold(n_splits=10, n_repeats=5, random_state=36851234)
n_scores = cross_val_score(pipeline, X_train, y_train, scoring='accuracy', cv=cv
np.mean(n_scores)
pipeline.fit(X_train,y_train)

print("Optimal number of features : %d" % rfecv.n_features_)
```

```
rfecv.support_rfecv_df = pd.DataFrame(rfecv.ranking_,index=X_train.columns,colum
rfecv.support_rfecv_df.head()

plt.figure(figsize=(12,6))
plt.xlabel("Number of features selected")
plt.ylabel("Cross validation score (nb of correct classifications)")
plt.plot(range(1, len(rfecv.grid_scores_) + 1), rfecv.grid_scores_)
plt.show()
```

```
Optimal number of features : 11
```



In [ ]: