In [ ]:
```
from sklearn.decomposition import PCA
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split, GridSearchCV, Stratifi
from sklearn.preprocessing import StandardScaler
from sklearn.svm import SVC
from sklearn.ensemble import RandomForestClassifier
from sklearn import metrics
import matplotlib.pyplot as plt
import seaborn as sns
from imblearn.pipeline import Pipeline
from imblearn.over_sampling import SMOTE
from sklearn.impute import SimpleImputer
```

In [ ]:
```
data = pd.read_csv('nba-player-stats-2021.csv', encoding='ISO-8859-1')
data.head()
```

Out[ ]:

	player	pos	age	tm	g	gs	mp	fg	fga	fgpercent	...	drb	trb	ast
0	Precious Achiuwa	C	22	TOR	73	28	1725	7.7	17.5	0.439	...	9.5	13.7	2.4
1	Steven Adams	C	28	MEM	76	75	1999	5.0	9.2	0.547	...	9.8	18.2	6.1
2	Bam Adebayo	C	24	MIA	56	56	1825	11.1	20.0	0.557	...	11.7	15.5	5.2
3	Santi Aldama	PF	21	MEM	32	0	360	7.0	17.5	0.402	...	7.2	11.6	2.8
4	LaMarcus Aldridge	C	36	BRK	47	12	1050	11.6	21.1	0.550	...	8.5	11.9	1.9

5 rows × 30 columns

In [ ]:
```
data = data.rename(columns={'player':'Player', 'pos':'Position', 'age':'Age'
                            'gs':'Game_Started', 'mp':'Minute_played', 'fg':
                            'fgpercent':'Field_goal%',
                            'x3p':'3points_scored', 'x3pa':'3points_Assists'
                            'x2pa':'2points_assits',
                            'x2ppercent':'2points%', 'ft':'FreeThrow', 'fta'
                            'ftpercent':'FreeThrow%', 'orb':'OffensiveRebour
                            'ast':'Assists', 'stl':'Steal', 'blk':'Blocks',
                            'pts':'Points', 'ortg':'OffensiveRating', 'drtg'
```

Basic understanding of data

```
In [ ]: print(data.describe())
```

```
              Age     N_Games  Game_Started  Minute_played  Field_goal  \
count  812.000000  812.000000    812.000000     812.000000  812.000000   
mean    26.051724   36.705665     16.672414     825.188424    6.935468   
std      4.059640   25.898042     23.817195     775.786331    3.419585   
min     19.000000    1.000000      0.000000       1.000000    0.000000   
25%     23.000000   12.000000      0.000000     121.000000    5.100000   
50%     25.000000   36.500000      4.000000     577.500000    6.850000   
75%     29.000000   61.000000     25.000000    1414.500000    8.600000   
max     41.000000   82.000000     82.000000    2854.000000   49.000000   

       Goal_attempt  Field_goal%  3points_scored  3points_Assists    3point
s%  \
count    812.000000   797.000000      812.000000       812.000000  740.00000
0   
mean      16.066995     0.434257        2.028695         6.467611    0.30344
5   
std        5.627889     0.137794        1.573494         4.443072    0.13811
1   
min        0.000000     0.000000        0.000000         0.000000    0.00000
0   
25%       12.600000     0.385000        0.600000         3.400000    0.25875
0   
50%       15.750000     0.441000        2.000000         6.550000    0.33100
0   
75%       19.200000     0.500000        3.100000         9.100000    0.37625
0   
max       49.700000     1.000000        9.900000        49.700000    1.00000
0   

       ...  DenffesiveRebound  TotalRebound     Assists       Steal  \
count  ...         812.000000    812.000000  812.000000  812.000000   
mean   ...           6.643966      9.068966    4.337685    1.591872   
std    ...           3.499107      5.043891    3.416246    1.731605   
min    ...           0.000000      0.000000    0.000000    0.000000   
25%    ...           4.700000      5.900000    2.300000    0.900000   
50%    ...           6.000000      7.800000    3.450000    1.400000   
75%    ...           8.300000     11.900000    6.000000    1.900000   
max    ...          48.500000     48.500000   49.000000   25.000000   

           Blocks    TurnOver  PersonalFoul      Points  OffensiveRating  \
count  812.000000  812.000000    812.000000  812.000000       802.000000   
mean     0.943103    2.534606      4.499015   18.794335       107.684539   
std      1.063908    2.046511      2.932605    8.559621        24.655914   
min      0.000000    0.000000      0.000000    0.000000         0.000000   
25%      0.300000    1.600000      3.175000   14.075000       101.000000   
50%      0.700000    2.300000      4.100000   18.700000       110.000000   
75%      1.225000    3.100000      5.425000   23.300000       118.000000   
max     16.600000   25.000000     48.800000   98.000000       232.000000   
```

```
       DeffensiveRating
count        812.000000
mean         112.289409
std            5.439612
min           63.000000
25%          110.000000
50%          113.000000
75%          116.000000
max          125.000000

[8 rows x 27 columns]
```

In [ ]:
```
print(f'Duplicate entries: {data.duplicated().sum()} \nNull values: \n{data.
```

```
Duplicate entries: 0
Null values:
Player                 0
Position               0
Age                    0
Team                   0
N_Games                0
Game_Started           0
Minute_played          0
Field_goal             0
Goal_attempt           0
Field_goal%           15
3points_scored         0
3points_Assists        0
3points%              72
2points_scored         0
2points_assits         0
2points%              28
FreeThrow              0
FreeThrowAttempt       0
FreeThrow%            97
OffensiveRebound       0
DenffesiveRebound      0
TotalRebound           0
Assists                0
Steal                  0
Blocks                 0
TurnOver               0
PersonalFoul           0
Points                 0
OffensiveRating       10
DeffensiveRating       0
dtype: int64
```

In [ ]:
```
data.shape
```

Out[ ]: (812, 30)

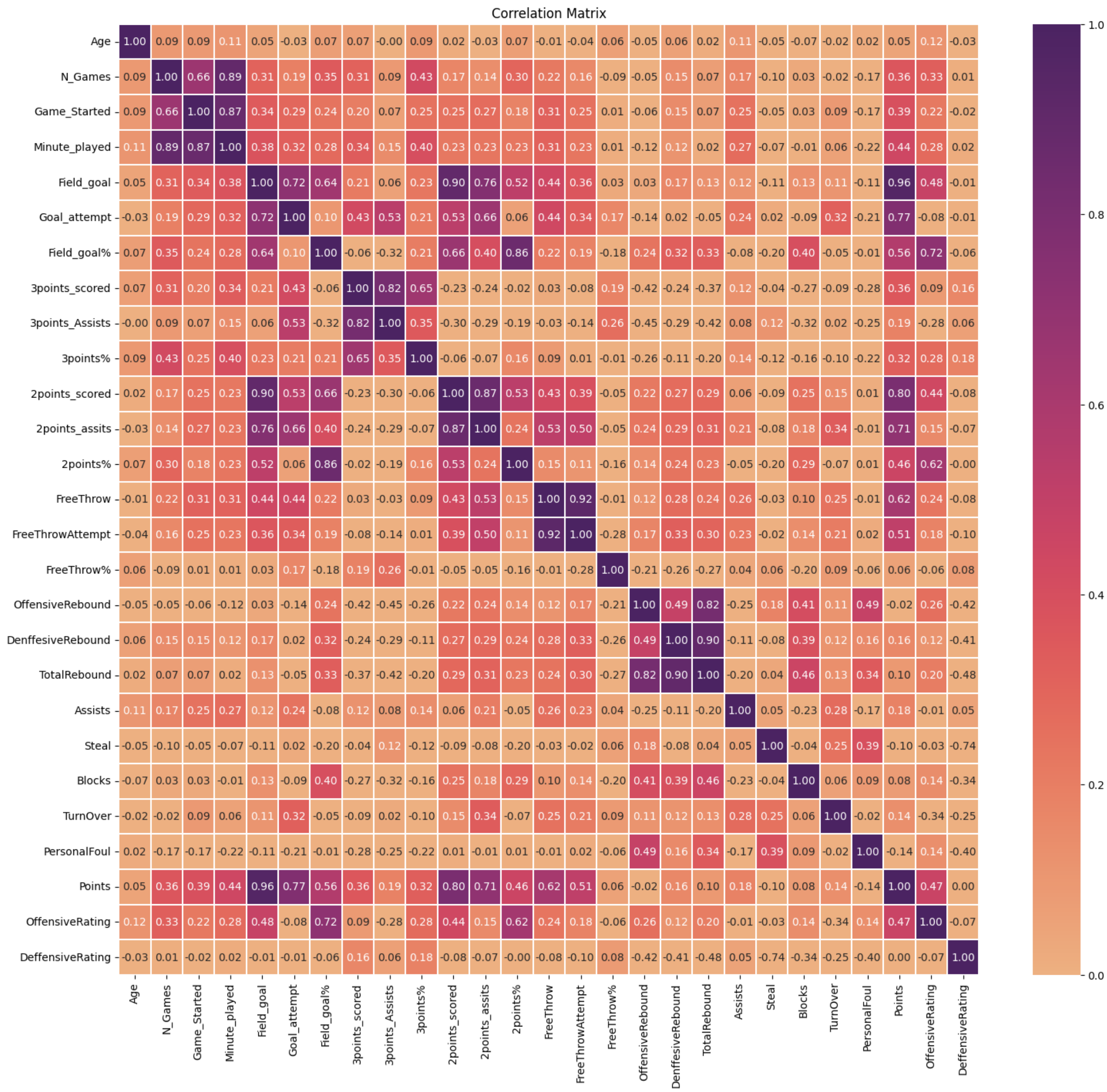
In [ ]:
```
# Drop all row with duplicate players
data = data.drop_duplicates(subset=['Player'])
data.shape
```

Out[ ]: (605, 30)

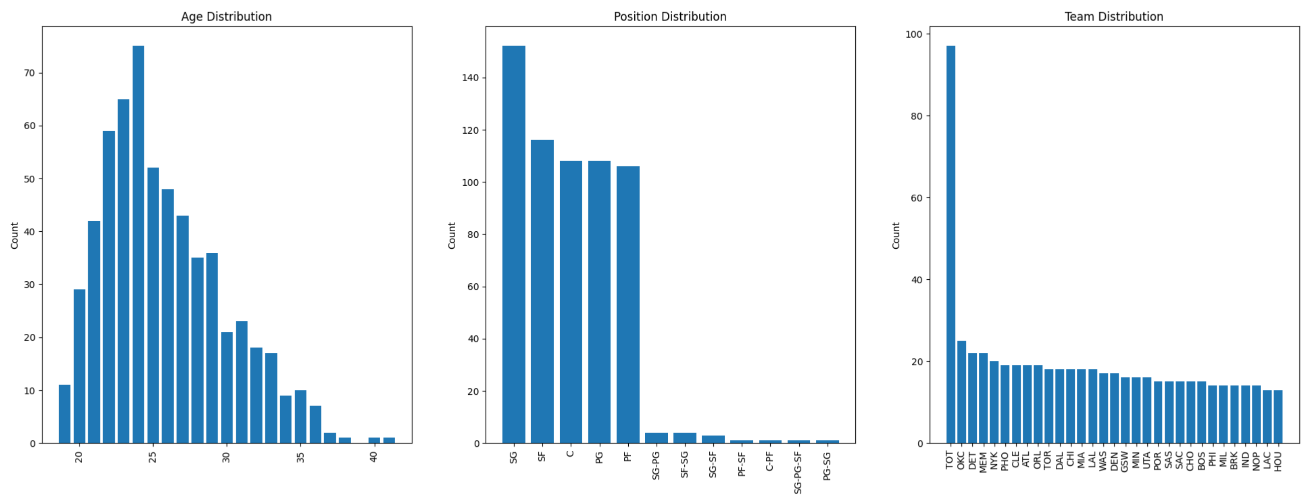
In [ ]:
```
# Fill all missing data with the most frequent rather than droping them sinc
imputer = SimpleImputer(strategy='most_frequent')
data = pd.DataFrame(imputer.fit_transform(data), columns=data.columns, index
```

Exploratory Data Analysis (EDA)

In [ ]:
```
# Create a heatmap to see how our feature are interacting with one another

plt.figure(figsize=(18,16))
corr = data.drop(columns=['Player', 'Position', 'Team']).corr(method='pearso
sns.heatmap(corr, annot=True, linewidth=.1, vmin=0, vmax=1,
            fmt=".2f", cmap=sns.color_palette("flare", as_cmap=True))
plt.title('Correlation Matrix')
plt.show()
```



In [ ]:
```python
# Create a figure and subplots to plot all categorical variable distributior
fig, axs = plt.subplots(nrows=1, ncols=3, figsize=(24, 8))
variables = ['Age', 'Position', 'Team']
for ax, var in zip(axs.flatten(), variables):
    counts = data[var].value_counts()
    ax.bar(counts.index, counts.values)
    ax.set_title(f'{var.capitalize()} Distribution')
    ax.set_ylabel('Count')
    ax.tick_params(axis='x', rotation=90)
```



In [ ]:
```
y = data['Position']

# Remove all lower classes in our target variable
class_count = y.value_counts()
rare_class = [cls for cls, count in class_count.items() if count <=4]
new_class_indice = [i for i, label in enumerate(y) if label not in rare_clas

data = data.iloc[new_class_indice]
```

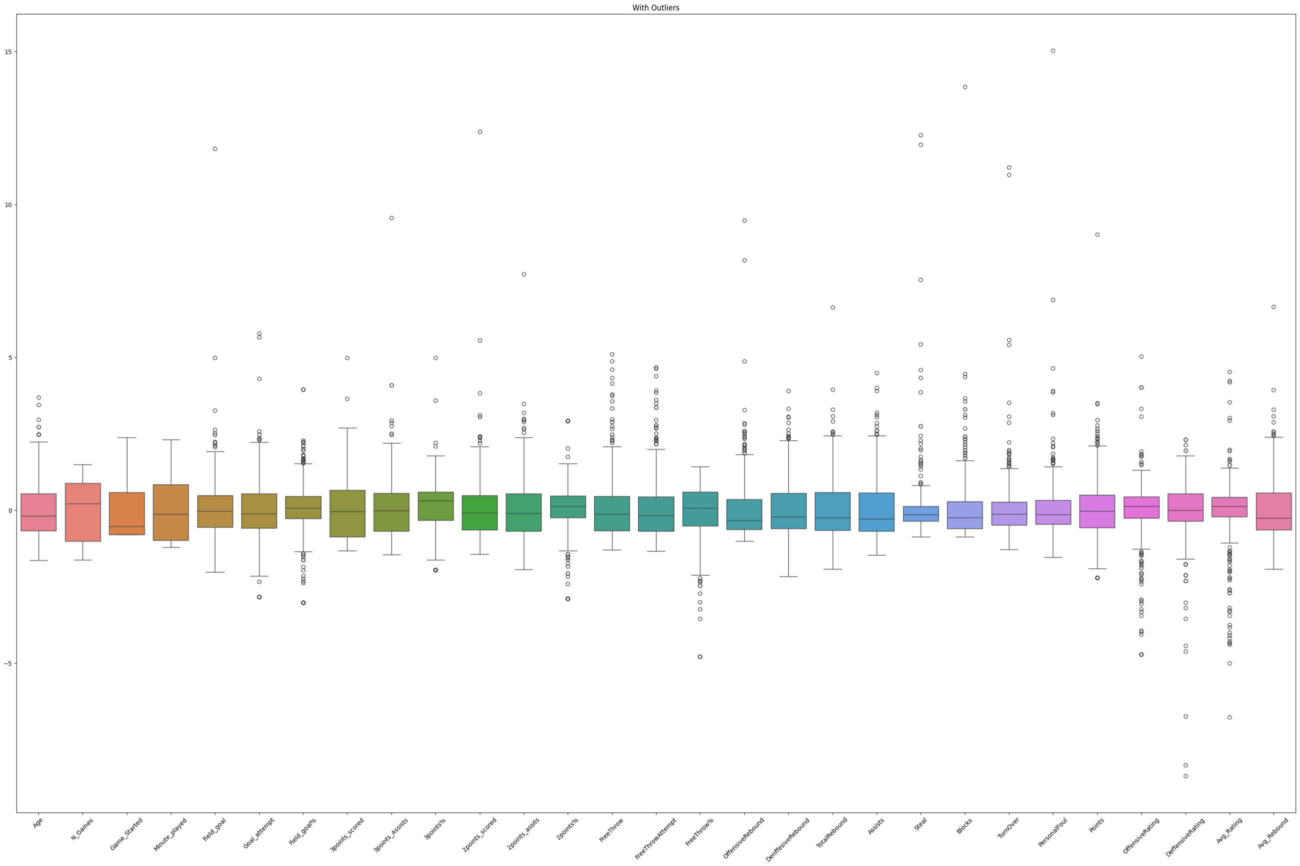
Feature Engineering

In [ ]:
```
# create some feature engineering
data['Avg_Rating'] = (data['OffensiveRating'] + data['DeffensiveRating'])/2
data['Avg_Rebound'] = (data['OffensiveRebound'] + data['DenffesiveRebound'])

# Drop features that are not relevent to our study
data = data.drop(columns=['Team'])
```

Identify and Remove outliers

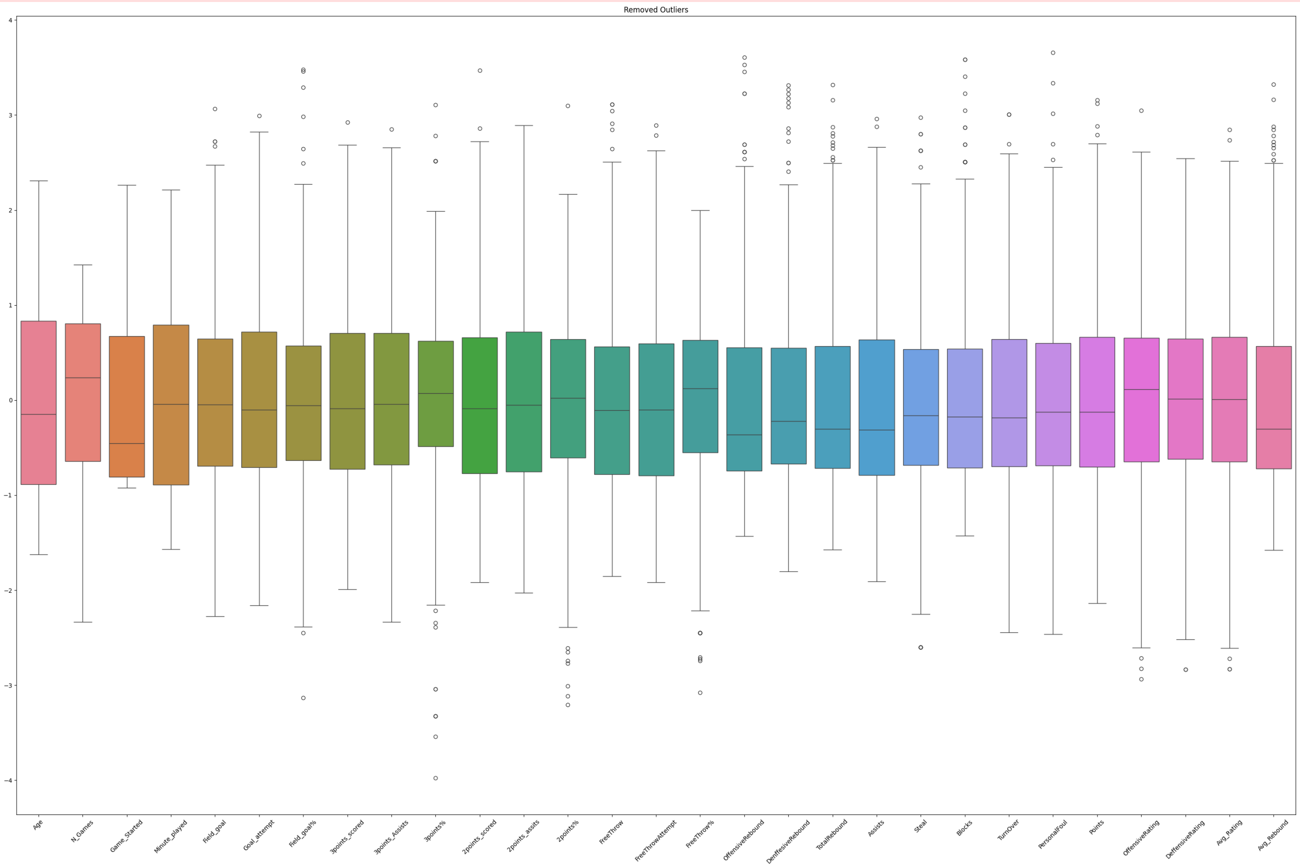
In [ ]:
```
# Get all the numerical columns and scale them
features = [col for col in data.columns if col not in ['Position', 'Player',
scaler = StandardScaler()
scaled_data = pd.DataFrame(scaler.fit_transform(data[features]), columns=fea

# Plot Boxplot
fig, ax = plt.subplots(figsize=(30,20))
sns.boxplot(data=scaled_data)
ax.set_xticklabels(ax.get_xticklabels(),rotation=45)
ax.set_title('With Outliers')
plt.tight_layout()
plt.show()
```

```
/var/folders/sb/73j4d15s4k34y66s1tpvsgx80000gn/T/ipykernel_6753/806505450.p
y:9: UserWarning: set_ticklabels() should only be used with a fixed number o
f ticks, i.e. after set_ticks() or using a FixedLocator.
  ax.set_xticklabels(ax.get_xticklabels(),rotation=45)
```



In [ ]:
```python
# Calculate outliers
Q1 = scaled_data.quantile(0.25)
Q3 = scaled_data.quantile(0.75)
IQR = Q3 - Q1
lower_bound = Q1 - 1.5 * IQR
upper_bound = Q3 + 1.5 * IQR

# identify outliers and mask it to the original data
mask = ~((scaled_data < lower_bound) | (scaled_data > upper_bound)).any(axis
filtered_data = data[mask].copy()

# scale the data and put on the dataframe to make easy to visualize
filtered_scaled_data = pd.DataFrame(scaler.fit_transform(filtered_data[featu

# boxplot
fig, ax = plt.subplots(figsize=(30,20))
sns.boxplot(data=filtered_scaled_data)
ax.set_xticklabels(ax.get_xticklabels(),rotation=45)
ax.set_title('Removed Outliers')
plt.tight_layout()
plt.show()
```

```
/var/folders/sb/73j4d15s4k34y66s1tpvsgx80000gn/T/ipykernel_6753/2772015398.p
y:18: UserWarning: set_ticklabels() should only be used with a fixed number
of ticks, i.e. after set_ticks() or using a FixedLocator.
  ax.set_xticklabels(ax.get_xticklabels(),rotation=45)
```



Principal Component Analysis (PCA)

In [ ]:
```
# Instanciate and fit pca
pca = PCA(n_components=10, random_state=42)
pca_components = pca.fit_transform(filtered_scaled_data)

# Create a label for the PCA columns
labels = [f'PC{i+1}' for i in range(pca.n_components_)]

# put the pca into a dataframe
pca_df = pd.DataFrame(pca_components, columns=labels)

# merge the filtered data with the pca data to indentify player performances
pca_merged = pd.concat([filtered_data.reset_index(drop=True), pca_df.reset_i

# Identify top and bottom players on PCA 1
top_players = pca_merged.sort_values(by='PC1', ascending=False).head(15)
bottom_players = pca_merged.sort_values(by='PC1', ascending=True).head(15)
```

```python
# Top / bottom feature contribution based on PCA 1
top_features = top_players[features]
bottom_features = bottom_players[features]

# Get the mean of each feature
mean_top_features = top_features.mean()
mean_bottom_features = bottom_features.mean()

# create a dataframe for comparison
feature_comparison = pd.DataFrame({
    'Top Performers': mean_top_features,
    'Bottom Performers': mean_bottom_features
})

# Print top players
print(top_players[['Player','Age','Field_goal%','PC1']])

print(feature_comparison.head(10))
```

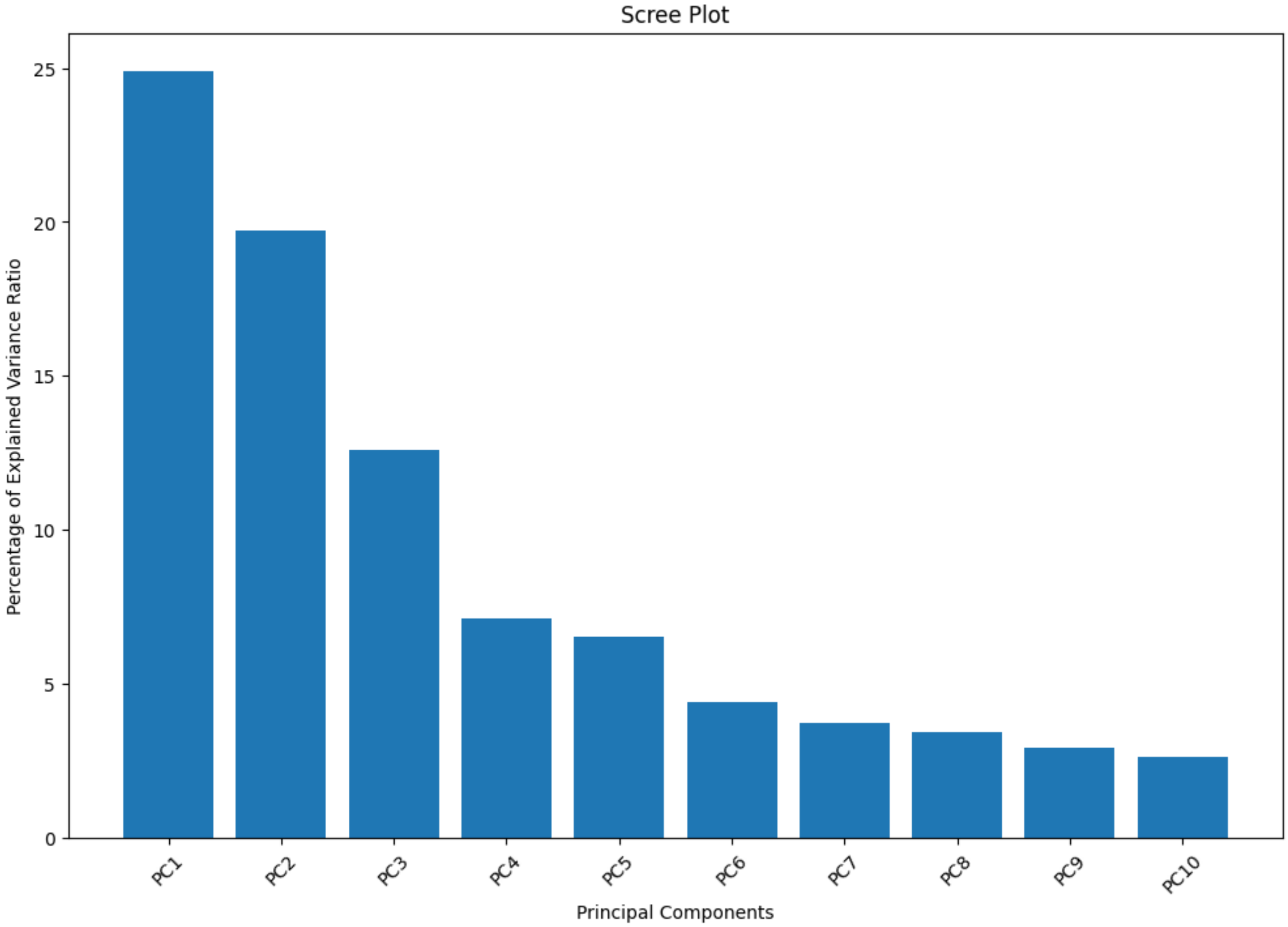
```
                  Player  Age  Field_goal%       PC1
345   Jonas ValanÄiÅ«nas   29        0.544  8.318119
343   Karl-Anthony Towns   26        0.529  8.273607
12         Deandre Ayton   23        0.634  8.020961
309     Domantas Sabonis   25        0.573  7.571184
139     Montrezl Harrell   28        0.645  7.422051
71        Brandon Clarke   25        0.644  6.852951
331         Jayson Tatum   23        0.453  6.584736
316         Pascal Siakam   27        0.494  6.379467
294        Julius Randle   27        0.411  5.614400
380       Christian Wood   26        0.501  5.580332
163       Brandon Ingram   24        0.461  5.539136
65     Wendell Carter Jr.   22        0.525  5.494160
39          Devin Booker   25        0.466  5.464489
105         Drew Eubanks   24        0.596  5.389534
86        Dewayne Dedmon   32        0.566  5.293341
```

Out[ ]:

	Top Performers	Bottom Performers
Age	25.733333	25.800000
N_Games	67.333333	24.933333
Game_Started	52.266667	2.866667
Minute_played	1985.000000	295.933333
Field_goal	10.913333	4.366667
Goal_attempt	20.833333	13.220000
Field_goal%	0.536133	0.337000
3points_scored	1.693333	2.426667
3points_Assists	4.733333	8.126667
3points%	0.331067	0.296133

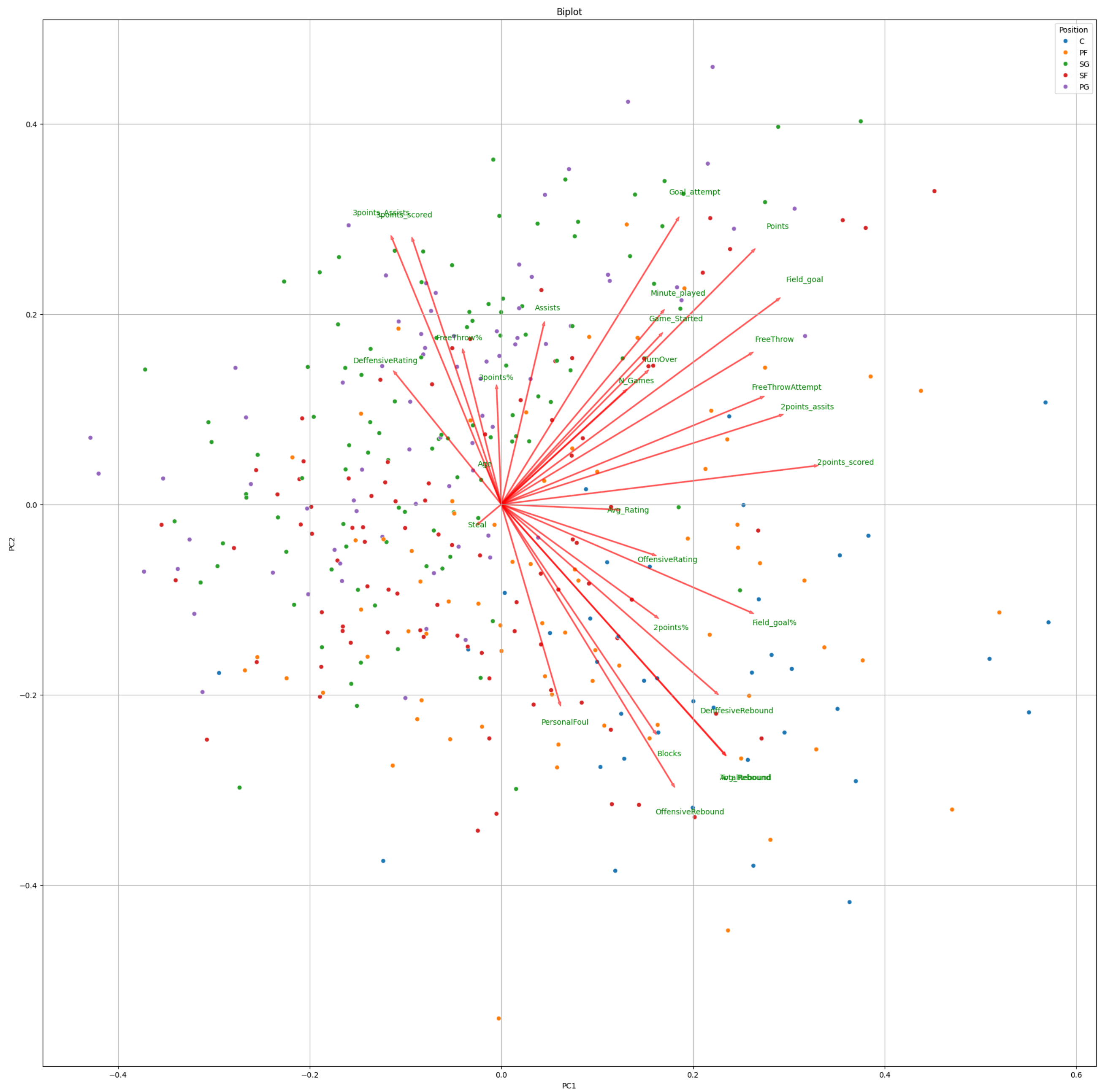
In [ ]:

```
# Plot the loading distributions
exp_var = np.round(pca.explained_variance_ratio_*100, decimals=1)
plt.figure(figsize=(12,8))
plt.bar(range(1, len(exp_var)+1), height=exp_var, tick_label=labels)

plt.ylabel('Percentage of Explained Variance Ratio')
plt.xlabel('Principal Components')
plt.title('Scree Plot')
plt.xticks(rotation=45)
plt.show()
```



In [ ]:
```
y = pca_merged['Position']

def myplot(score, coeff, labels, y):
    pc1 = score['PC1']
    pc2 = score['PC2']
    n = coeff.shape[0]
    # Scale the x and y to make the loadings easier to see
    scalex = 1/(pc1.max() - pc1.min())
    scaley = 1/(pc2.max() - pc2.min())
    plt.figure(figsize=(25,25))
    sns.scatterplot(x=pc1 * scalex, y=pc2 * scaley, hue=y)
    for i in range(n):
        # Plot an arrow for each component weight
        plt.arrow(0, 0, coeff[i, 0], coeff[i, 1], color='r', alpha=0.5)
        # Plot the name of the component (use 1.15 to plot the text slightly
        plt.text(coeff[i, 0] * 1.1, coeff[i, 1] * 1.1,
                 labels[i], color='g', ha='center', va='center')

    plt.xlabel("PC{}".format(1))
    plt.ylabel("PC{}".format(2))
    plt.title('Biplot')
    plt.grid()
```

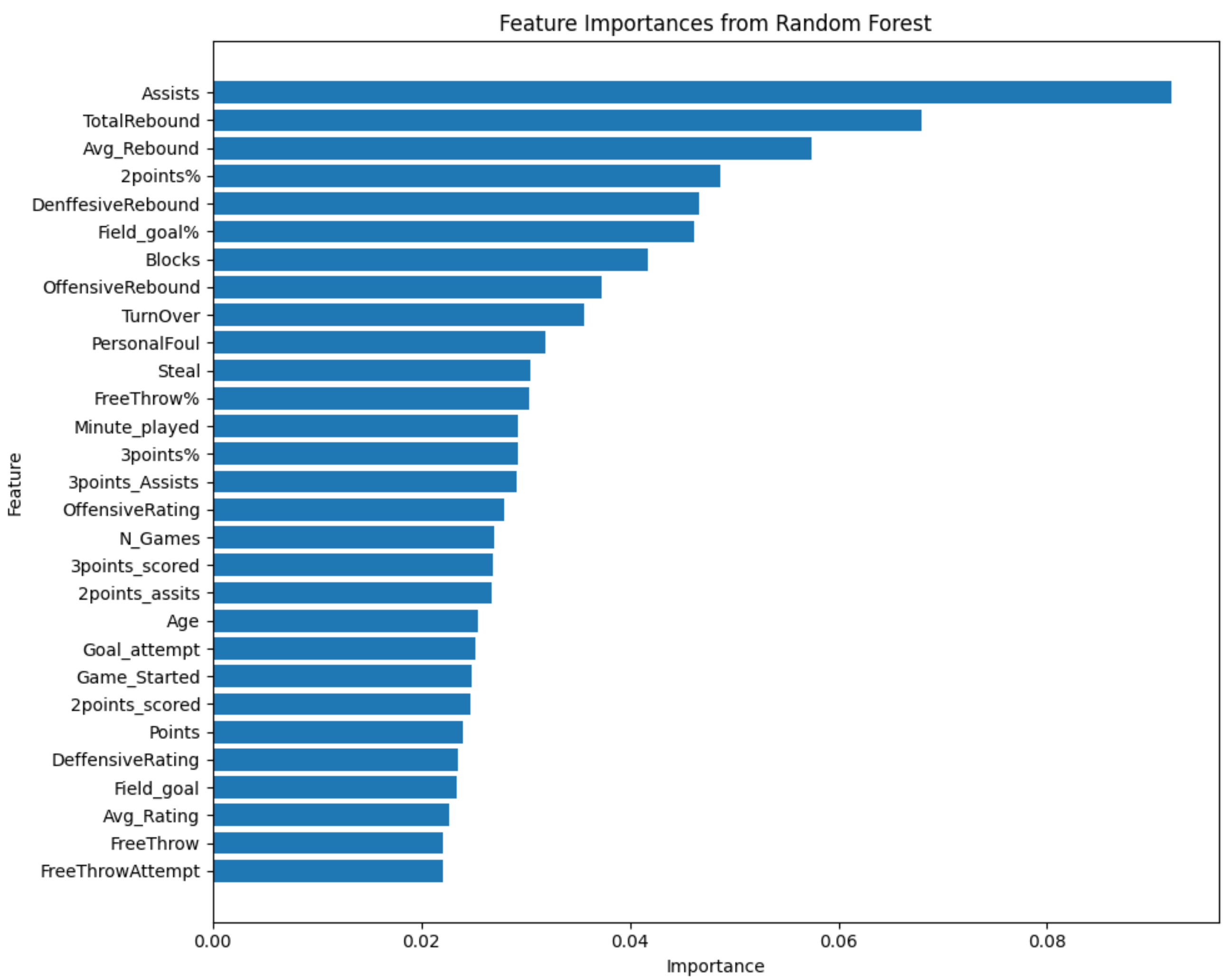
```
    plt.show()
# Call the function. Use only the 2 PCs.
myplot(pca_df, np.transpose(pca.components_), features, y)
```



Feature importance for classification

```
In [ ]: # create feature and target variables
X = filtered_data.drop(columns=['Position', 'Player'])
y = filtered_data['Position']

# Train Test Split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, rar
```

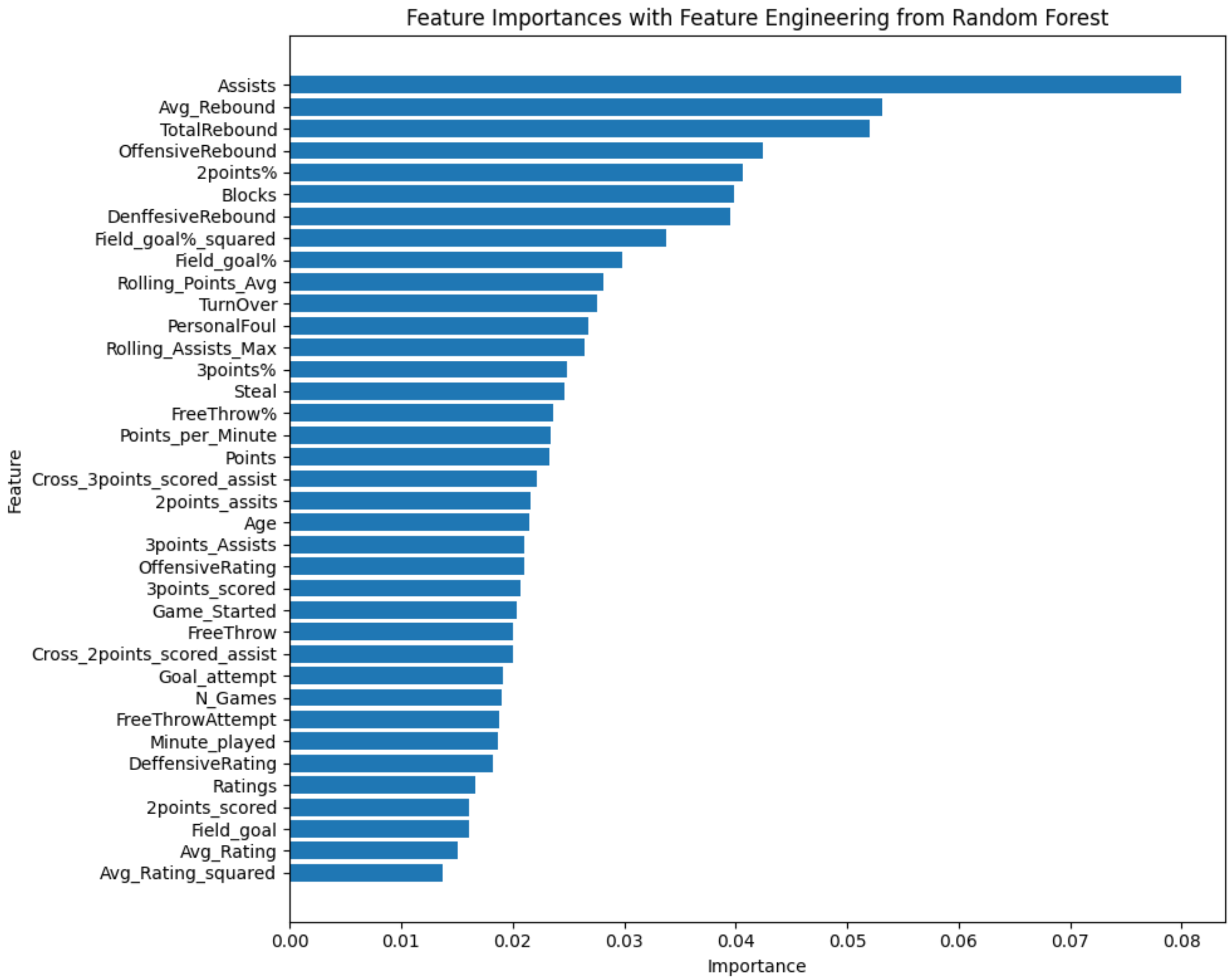
```
# Instanciate and fit model
rf_model = RandomForestClassifier(n_estimators=100, random_state=42)
rf_model.fit(X_train, y_train)

# Create a DataFrame for feature importance
importances = pd.DataFrame({
    'Feature': X.columns,
    'Importance': rf_model.feature_importances_
}).sort_values(by='Importance', ascending=False)

# Plot feature importance
plt.figure(figsize=(10,8))
plt.barh(importances['Feature'], importances['Importance'] )
plt.title("Feature Importances from Random Forest")
plt.xlabel('Importance')
plt.ylabel('Feature')
plt.gca().invert_yaxis()
plt.tight_layout()
plt.show()
```



More Feature Engineering

In [ ]:
```
# Interaction features
filtered_data['Points_per_Minute'] = filtered_data['Points'] / filtered_data

# Polynomial features
filtered_data['Field_goal%_squared'] = filtered_data['Field_goal%'] ** 2
filtered_data['Avg_Rating_squared'] = filtered_data['Avg_Rating'] ** 2

# Aggregated statistics
filtered_data['Rolling_Points_Avg'] = filtered_data['Points'].rolling(window
filtered_data['Rolling_Assists_Max'] = filtered_data['Assists'].rolling(winc

# Cross Features
filtered_data['Cross_2points_scored_assist'] = filtered_data['2points_assits
filtered_data['Cross_3points_scored_assist'] = filtered_data['3points_Assist
filtered_data['Ratings'] = filtered_data['DeffensiveRating'] * filtered_data
```

In [ ]:
```
# create feature and target variables
X = filtered_data.drop(columns=['Position', 'Player'])
y = filtered_data['Position']

# Train Test Split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, rar

# Instanciate and fit model
rf_model = RandomForestClassifier(n_estimators=100, random_state=42)
rf_model.fit(X_train, y_train)

# Create a DataFrame for feature importance
importances = pd.DataFrame({
    'Feature': X.columns,
    'Importance': rf_model.feature_importances_
}).sort_values(by='Importance', ascending=False)

# Plot feature importance
plt.figure(figsize=(10,8))
plt.barh(importances['Feature'], importances['Importance'] )
plt.title("Feature Importances with Feature Engineering from Random Forest")
plt.xlabel('Importance')
plt.ylabel('Feature')
plt.gca().invert_yaxis()
plt.tight_layout()
plt.show()
```



In [ ]:
```
# fill and NA values based on the feature engineering and reset the index
filtered_data = filtered_data.fillna(0)
filtered_data = filtered_data.reset_index(drop=True)
```

```
/var/folders/sb/73j4d15s4k34y66s1tpvsgx80000gn/T/ipykernel_6753/122167782.p
y:2: FutureWarning: Downcasting object dtype arrays on .fillna, .ffill, .bfi
ll is deprecated and will change in a future version. Call result.infer_obje
cts(copy=False) instead. To opt-in to the future behavior, set `pd.set_optio
n('future.no_silent_downcasting', True)`
  filtered_data = filtered_data.fillna(0)
```

Model Training, Test and Evaluation

In [ ]:
```
# Top 34 features
importances['Feature'].head(34).values
```

Out[ ]:
```
array(['Assists', 'Avg_Rebound', 'TotalRebound', 'OffensiveRebound',
       '2points%', 'Blocks', 'DenffesiveRebound', 'Field_goal%_squared',
       'Field_goal%', 'Rolling_Points_Avg', 'TurnOver', 'PersonalFoul',
       'Rolling_Assists_Max', '3points%', 'Steal', 'FreeThrow%',
       'Points_per_Minute', 'Points', 'Cross_3points_scored_assist',
       '2points_assits', 'Age', '3points_Assists', 'OffensiveRating',
       '3points_scored', 'Game_Started', 'FreeThrow',
       'Cross_2points_scored_assist', 'Goal_attempt', 'N_Games',
       'FreeThrowAttempt', 'Minute_played', 'DeffensiveRating', 'Ratings',
       '2points_scored'], dtype=object)
```

In [ ]:
```
# Split features and target variables
top_features = ['Assists', 'Avg_Rebound', 'TotalRebound', 'OffensiveRebound'
       '2points%', 'Blocks', 'DenffesiveRebound', 'Field_goal%_squared',
       'Field_goal%', 'Rolling_Points_Avg', 'TurnOver', 'PersonalFoul',
       'Rolling_Assists_Max', '3points%', 'Steal', 'FreeThrow%',
       'Points_per_Minute', 'Points', 'Cross_3points_scored_assist',
       '2points_assits', 'Age', '3points_Assists', 'OffensiveRating',
       '3points_scored', 'Game_Started', 'FreeThrow',
       'Cross_2points_scored_assist', 'Goal_attempt', 'N_Games',
       'FreeThrowAttempt', 'Minute_played', 'DeffensiveRating', 'Ratings',
       '2points_scored']

X = filtered_data[top_features]
y = filtered_data['Position']


# Split the data before any preprocessing
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.20, ra

# Create pipelines for each classifier to eliminate data leakage
svc_pipeline = Pipeline(steps=[
    ('scaler', StandardScaler()),
    ('smote', SMOTE(random_state=42)),
    ('svc', SVC(class_weight='balanced', random_state=42))
])

rf_pipeline = Pipeline(steps=[
    ('scaler', StandardScaler()),
    ('smote', SMOTE(random_state=42)),
    ('rf', RandomForestClassifier(class_weight='balanced', random_state=42))
])


# Define classifiers
classifiers = {
    'SVC': svc_pipeline,
    'RandomForestClassifier': rf_pipeline
}
```

```
# Define hyperparameters
params = {
    'SVC': {
        'svc__kernel': ['linear', 'poly', 'rbf', 'sigmoid'],
        'svc__degree': [1, 2, 3, 4],
        'svc__C': [1, 10, 100, 200, 300],
        'svc__gamma': [0.1, 0.01, 0.001, 1]
    },
    'RandomForestClassifier': {
        'rf__n_estimators': [1, 10, 100, 200, 500, 600],
        'rf__max_depth': [10, 50, 100, 200, 400, 500],
        'rf__bootstrap': [True],
        'rf__max_features': ['sqrt', 'log2'],
        'rf__criterion': ['gini', 'entropy']
    }
}
# Define different KFold strategies
kfold_strategies = {
    'StratifiedKFold_3': StratifiedKFold(n_splits=3),
    'StratifiedKFold_5': StratifiedKFold(n_splits=5),
    'StratifiedKFold_10': StratifiedKFold(n_splits=10),
    'StratifiedKFold_20': StratifiedKFold(n_splits=20),
    'KFold_3': KFold(n_splits=3, shuffle=True, random_state=42),
    'KFold_5': KFold(n_splits=5, shuffle=True, random_state=42),
    'KFold_10': KFold(n_splits=10, shuffle=True, random_state=42),
    'KFold_20': KFold(n_splits=20, shuffle=True, random_state=42)
}

# Perform cross-validation and grid search
for kfold_name, kfold_strategy in kfold_strategies.items():
    print(f'Using KFold strategy: {kfold_name}')

    for name, clf in classifiers.items():
        print(f'Classifier: {name}')
        grid_best_model = GridSearchCV(estimator=clf, param_grid=params[name
                                       cv=kfold_strategy, verbose=1)

        grid_best_model.fit(X_train, y_train)

        y_pred = grid_best_model.predict(X_test)

        print(f'Best Score: {grid_best_model.best_score_}')
        print(f'Best Parameters: {grid_best_model.best_params_}')

        metrics.ConfusionMatrixDisplay.from_predictions(y_test, y_pred, norm
        print(metrics.classification_report(y_test, y_pred))
        print('-' * 75)
```

```
Using KFold strategy: StratifiedKFold_3
Classifier: SVC
```

```
Fitting 3 folds for each of 320 candidates, totalling 960 fits
Best Score: 0.5228758169934641
Best Parameters: {'svc__C': 1, 'svc__degree': 1, 'svc__gamma': 0.01, 'svc__k
ernel': 'poly'}
              precision    recall  f1-score   support

           C       0.42      0.62      0.50         8
          PF       0.25      0.31      0.28        13
          PG       0.60      0.69      0.64        13
          SF       0.17      0.11      0.13        18
          SG       0.59      0.52      0.55        25

    accuracy                           0.43        77
   macro avg       0.40      0.45      0.42        77
weighted avg       0.42      0.43      0.42        77

---------------------------------------------------------------------------
Classifier: RandomForestClassifier
Fitting 3 folds for each of 144 candidates, totalling 432 fits
Best Score: 0.5
Best Parameters: {'rf__bootstrap': True, 'rf__criterion': 'gini', 'rf__max_d
epth': 10, 'rf__max_features': 'sqrt', 'rf__n_estimators': 100}
              precision    recall  f1-score   support

           C       0.50      0.75      0.60         8
          PF       0.25      0.23      0.24        13
          PG       0.64      0.69      0.67        13
          SF       0.26      0.28      0.27        18
          SG       0.55      0.44      0.49        25

    accuracy                           0.44        77
   macro avg       0.44      0.48      0.45        77
weighted avg       0.44      0.44      0.44        77

---------------------------------------------------------------------------
Using KFold strategy: StratifiedKFold_5
Classifier: SVC
Fitting 5 folds for each of 320 candidates, totalling 1600 fits
Best Score: 0.5358011634056055
Best Parameters: {'svc__C': 10, 'svc__degree': 1, 'svc__gamma': 0.001, 'svc_
_kernel': 'rbf'}
              precision    recall  f1-score   support

           C       0.45      0.62      0.53         8
          PF       0.35      0.46      0.40        13
          PG       0.53      0.62      0.57        13
          SF       0.21      0.17      0.19        18
          SG       0.65      0.52      0.58        25

    accuracy                           0.45        77
```

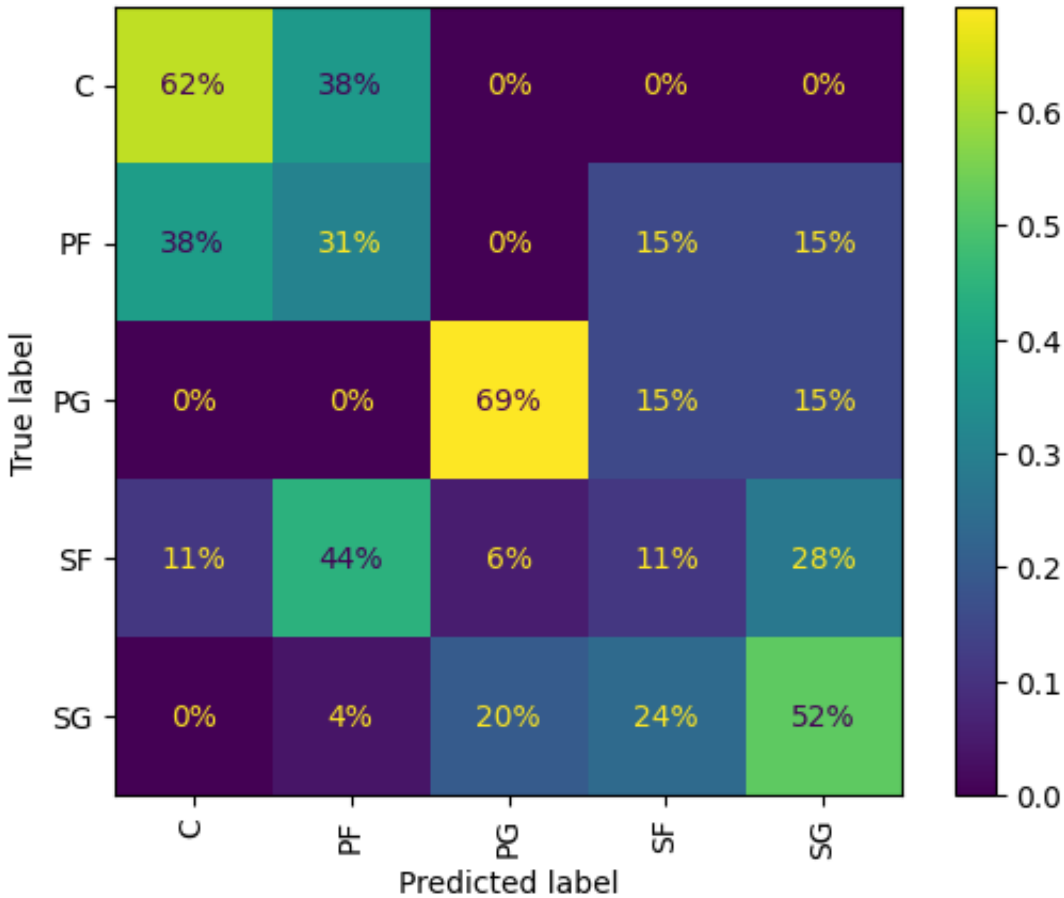
```
   macro avg       0.44      0.48      0.45        77
weighted avg       0.46      0.45      0.45        77

---------------------------------------------------------------------------
Classifier: RandomForestClassifier
Fitting 5 folds for each of 144 candidates, totalling 720 fits
Best Score: 0.48995240613432045
Best Parameters: {'rf__bootstrap': True, 'rf__criterion': 'entropy', 'rf__ma
x_depth': 50, 'rf__max_features': 'sqrt', 'rf__n_estimators': 500}
              precision    recall  f1-score   support

           C       0.50      0.75      0.60         8
          PF       0.33      0.31      0.32        13
          PG       0.62      0.62      0.62        13
          SF       0.37      0.39      0.38        18
          SG       0.57      0.48      0.52        25

    accuracy                           0.48        77
   macro avg       0.48      0.51      0.49        77
weighted avg       0.48      0.48      0.48        77

---------------------------------------------------------------------------
Using KFold strategy: StratifiedKFold_10
Classifier: SVC
Fitting 10 folds for each of 320 candidates, totalling 3200 fits
Best Score: 0.5494623655913978
Best Parameters: {'svc__C': 10, 'svc__degree': 1, 'svc__gamma': 0.001, 'svc_
_kernel': 'rbf'}
              precision    recall  f1-score   support

           C       0.45      0.62      0.53         8
          PF       0.35      0.46      0.40        13
          PG       0.53      0.62      0.57        13
          SF       0.21      0.17      0.19        18
          SG       0.65      0.52      0.58        25

    accuracy                           0.45        77
   macro avg       0.44      0.48      0.45        77
weighted avg       0.46      0.45      0.45        77

---------------------------------------------------------------------------
Classifier: RandomForestClassifier
Fitting 10 folds for each of 144 candidates, totalling 1440 fits
Best Score: 0.47408602150537626
Best Parameters: {'rf__bootstrap': True, 'rf__criterion': 'entropy', 'rf__ma
x_depth': 10, 'rf__max_features': 'sqrt', 'rf__n_estimators': 500}
              precision    recall  f1-score   support

           C       0.50      0.75      0.60         8
          PF       0.36      0.38      0.37        13
```

```
          PG       0.67      0.77      0.71        13
          SF       0.38      0.33      0.35        18
          SG       0.60      0.48      0.53        25

    accuracy                           0.51        77
   macro avg       0.50      0.54      0.51        77
weighted avg       0.51      0.51      0.50        77

---------------------------------------------------------------------------
Using KFold strategy: StratifiedKFold_20
Classifier: SVC
Fitting 20 folds for each of 320 candidates, totalling 6400 fits
Best Score: 0.5364583333333333
Best Parameters: {'svc__C': 10, 'svc__degree': 1, 'svc__gamma': 0.001, 'svc_
_kernel': 'rbf'}
              precision    recall  f1-score   support

           C       0.45      0.62      0.53         8
          PF       0.35      0.46      0.40        13
          PG       0.53      0.62      0.57        13
          SF       0.21      0.17      0.19        18
          SG       0.65      0.52      0.58        25

    accuracy                           0.45        77
   macro avg       0.44      0.48      0.45        77
weighted avg       0.46      0.45      0.45        77

---------------------------------------------------------------------------
Classifier: RandomForestClassifier
Fitting 20 folds for each of 144 candidates, totalling 2880 fits
Best Score: 0.49083333333333323
Best Parameters: {'rf__bootstrap': True, 'rf__criterion': 'gini', 'rf__max_d
epth': 10, 'rf__max_features': 'sqrt', 'rf__n_estimators': 600}
              precision    recall  f1-score   support

           C       0.55      0.75      0.63         8
          PF       0.38      0.38      0.38        13
          PG       0.60      0.69      0.64        13
          SF       0.39      0.39      0.39        18
          SG       0.60      0.48      0.53        25

    accuracy                           0.51        77
   macro avg       0.50      0.54      0.52        77
weighted avg       0.51      0.51      0.50        77

---------------------------------------------------------------------------
Using KFold strategy: KFold_3
Classifier: SVC
Fitting 3 folds for each of 320 candidates, totalling 960 fits
Best Score: 0.4901960784313726
```

```
Best Parameters: {'svc__C': 10, 'svc__degree': 1, 'svc__gamma': 0.001, 'svc_
_kernel': 'rbf'}
              precision    recall  f1-score   support

           C       0.45      0.62      0.53         8
          PF       0.35      0.46      0.40        13
          PG       0.53      0.62      0.57        13
          SF       0.21      0.17      0.19        18
          SG       0.65      0.52      0.58        25

    accuracy                           0.45        77
   macro avg       0.44      0.48      0.45        77
weighted avg       0.46      0.45      0.45        77

---------------------------------------------------------------------------
Classifier: RandomForestClassifier
Fitting 3 folds for each of 144 candidates, totalling 432 fits
Best Score: 0.4411764705882353
Best Parameters: {'rf__bootstrap': True, 'rf__criterion': 'gini', 'rf__max_d
epth': 10, 'rf__max_features': 'sqrt', 'rf__n_estimators': 200}
              precision    recall  f1-score   support

           C       0.50      0.75      0.60         8
          PF       0.38      0.38      0.38        13
          PG       0.57      0.62      0.59        13
          SF       0.28      0.28      0.28        18
          SG       0.50      0.40      0.44        25

    accuracy                           0.44        77
   macro avg       0.45      0.49      0.46        77
weighted avg       0.44      0.44      0.44        77

---------------------------------------------------------------------------
Using KFold strategy: KFold_5
Classifier: SVC
Fitting 5 folds for each of 320 candidates, totalling 1600 fits
Best Score: 0.5162876784769963
Best Parameters: {'svc__C': 10, 'svc__degree': 1, 'svc__gamma': 0.001, 'svc_
_kernel': 'rbf'}
              precision    recall  f1-score   support

           C       0.45      0.62      0.53         8
          PF       0.35      0.46      0.40        13
          PG       0.53      0.62      0.57        13
          SF       0.21      0.17      0.19        18
          SG       0.65      0.52      0.58        25

    accuracy                           0.45        77
   macro avg       0.44      0.48      0.45        77
weighted avg       0.46      0.45      0.45        77
```

```
--------------------------------------------------------------------------
Classifier: RandomForestClassifier
Fitting 5 folds for each of 144 candidates, totalling 720 fits
Best Score: 0.49365415124272866
Best Parameters: {'rf__bootstrap': True, 'rf__criterion': 'gini', 'rf__max_d
epth': 10, 'rf__max_features': 'sqrt', 'rf__n_estimators': 10}
              precision    recall  f1-score   support

           C       0.44      0.50      0.47         8
          PF       0.38      0.46      0.41        13
          PG       0.69      0.69      0.69        13
          SF       0.33      0.28      0.30        18
          SG       0.54      0.52      0.53        25

    accuracy                           0.48        77
   macro avg       0.48      0.49      0.48        77
weighted avg       0.48      0.48      0.48        77

--------------------------------------------------------------------------
Using KFold strategy: KFold_10
Classifier: SVC
Fitting 10 folds for each of 320 candidates, totalling 3200 fits
Best Score: 0.520752688172043
Best Parameters: {'svc__C': 1, 'svc__degree': 1, 'svc__gamma': 0.01, 'svc__k
ernel': 'sigmoid'}
              precision    recall  f1-score   support

           C       0.38      0.62      0.48         8
          PF       0.25      0.31      0.28        13
          PG       0.62      0.77      0.69        13
          SF       0.18      0.11      0.14        18
          SG       0.62      0.52      0.57        25

    accuracy                           0.44        77
   macro avg       0.41      0.47      0.43        77
weighted avg       0.43      0.44      0.43        77

--------------------------------------------------------------------------
Classifier: RandomForestClassifier
Fitting 10 folds for each of 144 candidates, totalling 1440 fits
Best Score: 0.4904301075268817
Best Parameters: {'rf__bootstrap': True, 'rf__criterion': 'gini', 'rf__max_d
epth': 50, 'rf__max_features': 'sqrt', 'rf__n_estimators': 100}
              precision    recall  f1-score   support

           C       0.40      0.50      0.44         8
          PF       0.29      0.31      0.30        13
          PG       0.57      0.62      0.59        13
          SF       0.26      0.28      0.27        18
```

```
          SG       0.50      0.40      0.44        25

    accuracy                           0.40        77
   macro avg       0.40      0.42      0.41        77
weighted avg       0.41      0.40      0.40        77

---------------------------------------------------------------------------
Using KFold strategy: KFold_20
Classifier: SVC
Fitting 20 folds for each of 320 candidates, totalling 6400 fits
Best Score: 0.540625
Best Parameters: {'svc__C': 1, 'svc__degree': 1, 'svc__gamma': 0.01, 'svc__k
ernel': 'poly'}
              precision    recall  f1-score   support

           C       0.42      0.62      0.50         8
          PF       0.25      0.31      0.28        13
          PG       0.60      0.69      0.64        13
          SF       0.17      0.11      0.13        18
          SG       0.59      0.52      0.55        25

    accuracy                           0.43        77
   macro avg       0.40      0.45      0.42        77
weighted avg       0.42      0.43      0.42        77

---------------------------------------------------------------------------
Classifier: RandomForestClassifier
Fitting 20 folds for each of 144 candidates, totalling 2880 fits
Best Score: 0.4872916666666667
Best Parameters: {'rf__bootstrap': True, 'rf__criterion': 'gini', 'rf__max_d
epth': 50, 'rf__max_features': 'sqrt', 'rf__n_estimators': 600}
              precision    recall  f1-score   support

           C       0.50      0.75      0.60         8
          PF       0.36      0.38      0.37        13
          PG       0.60      0.69      0.64        13
          SF       0.33      0.28      0.30        18
          SG       0.57      0.48      0.52        25

    accuracy                           0.48        77
   macro avg       0.47      0.52      0.49        77
weighted avg       0.48      0.48      0.47        77

---------------------------------------------------------------------------
```



C
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True label
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Predicted label
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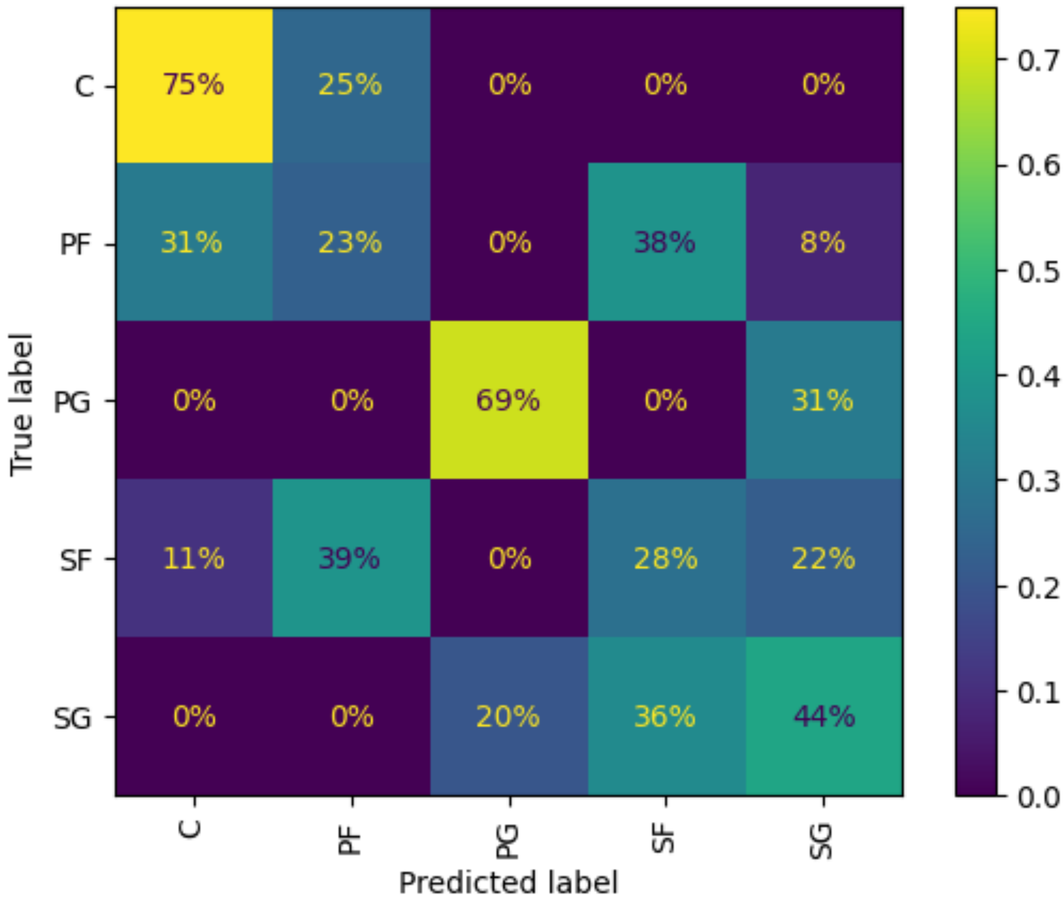

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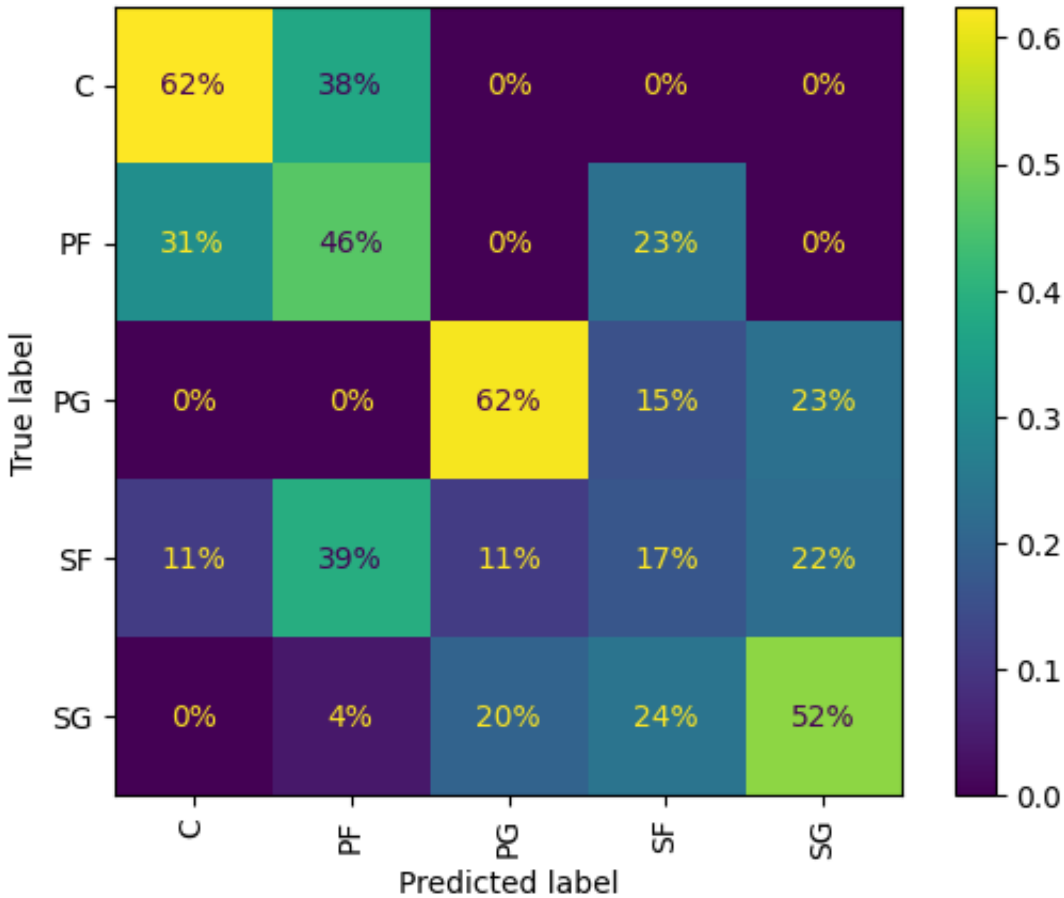

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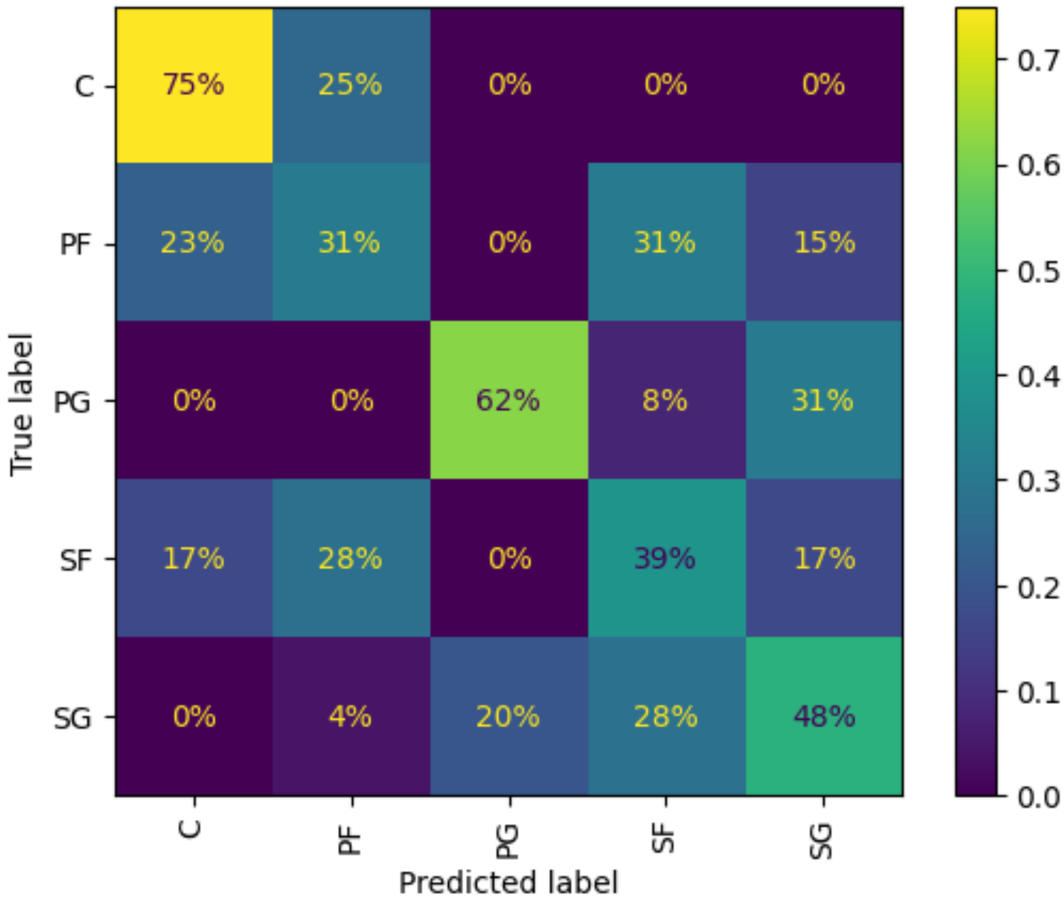
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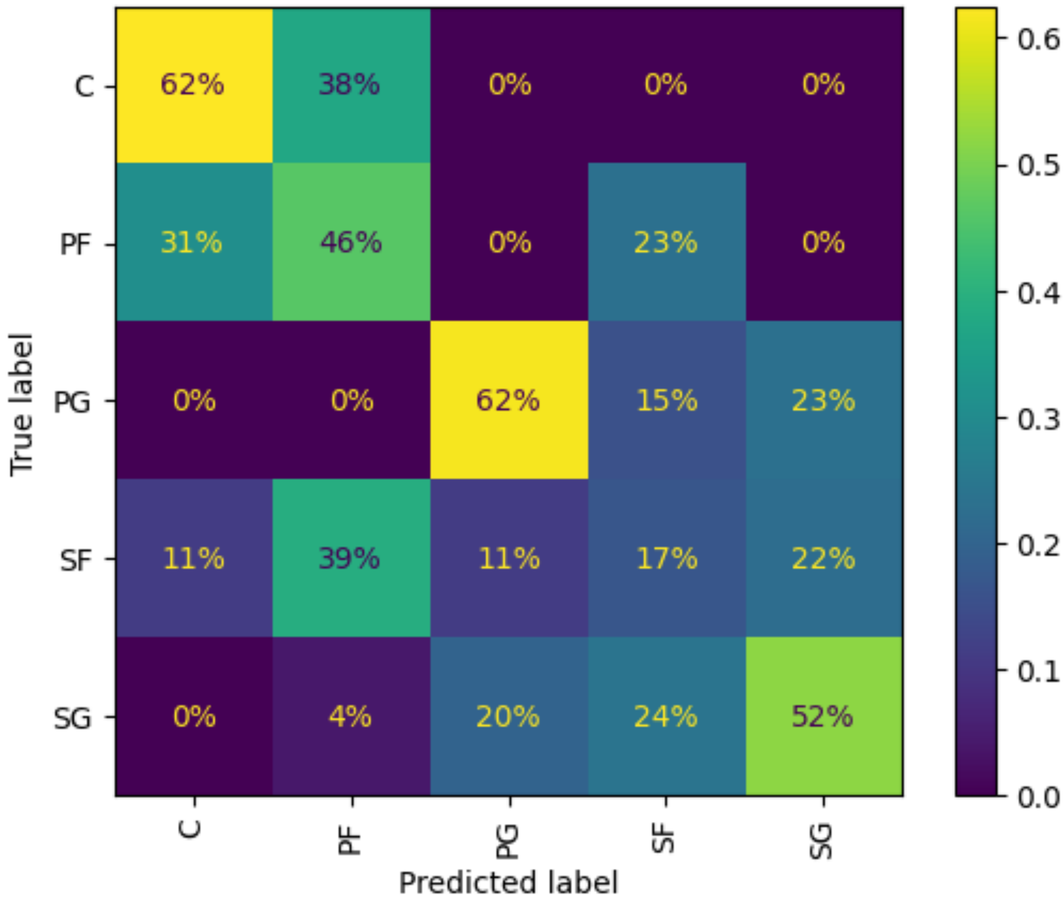
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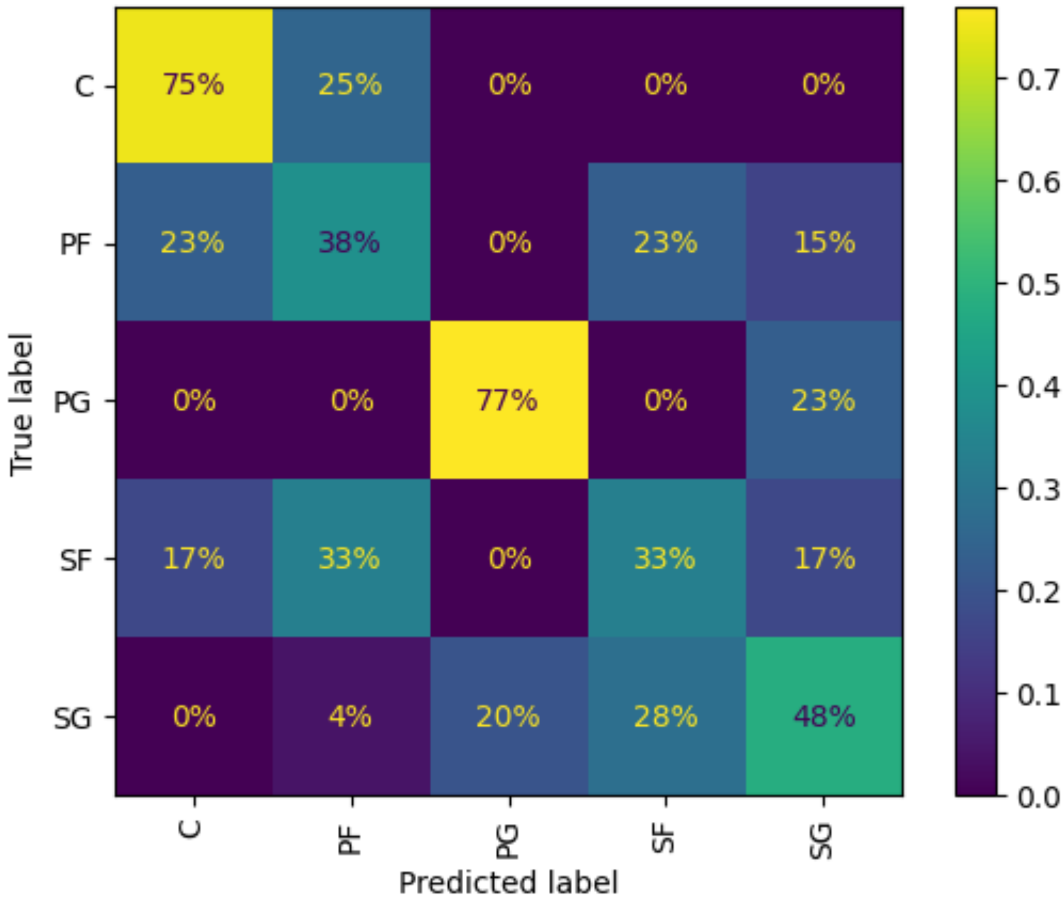

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Predicted label
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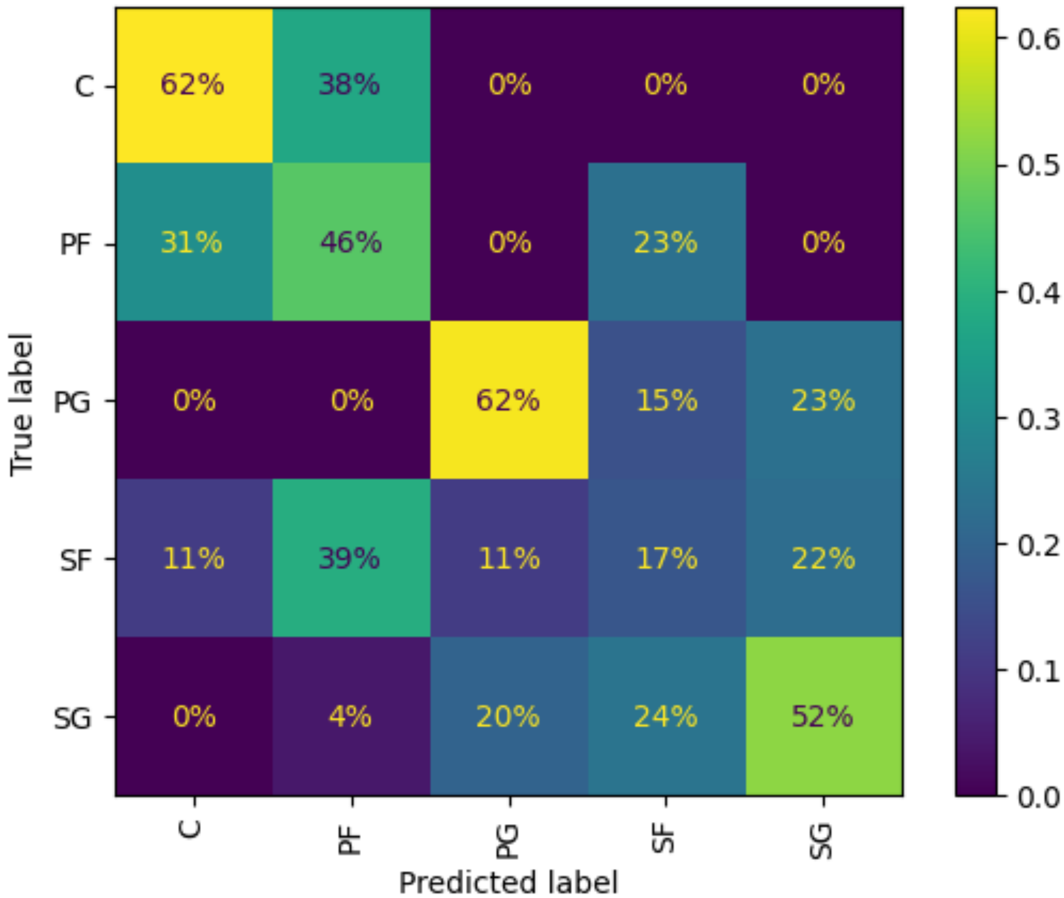
C
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True label
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Predicted label
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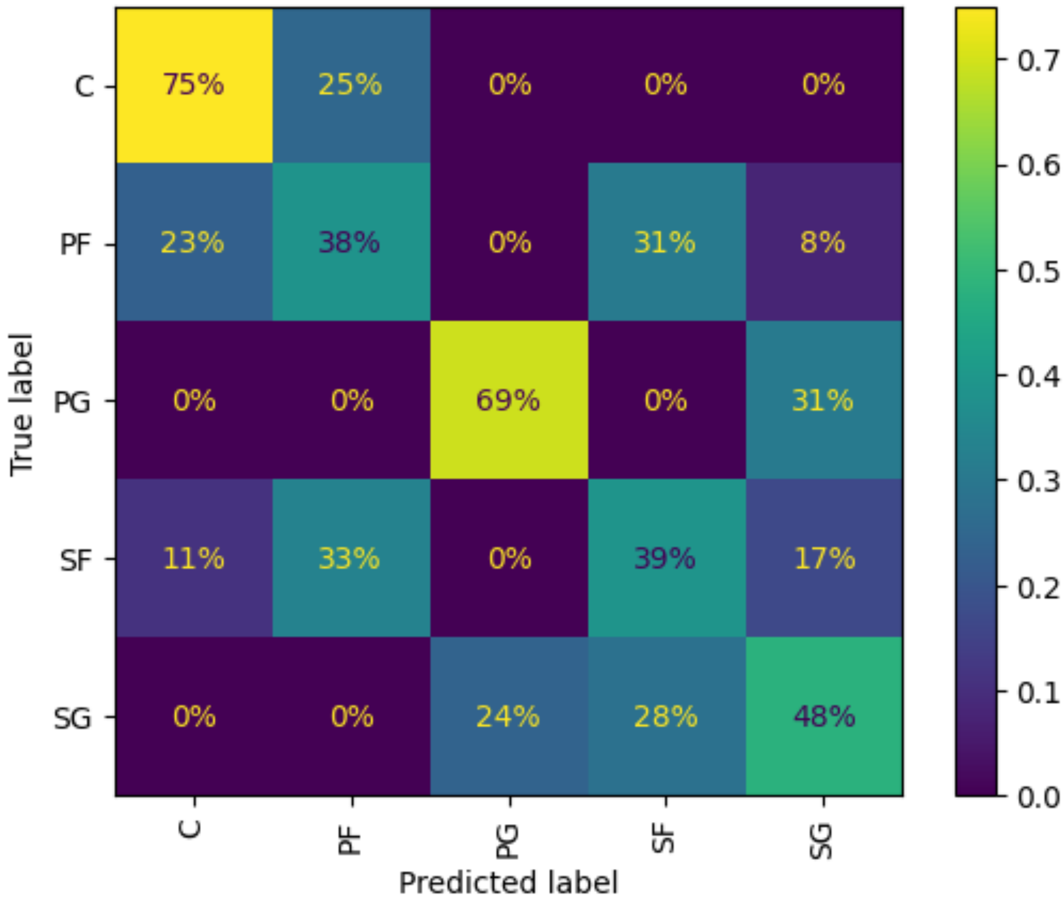
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SG
True label
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Predicted label
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0.2
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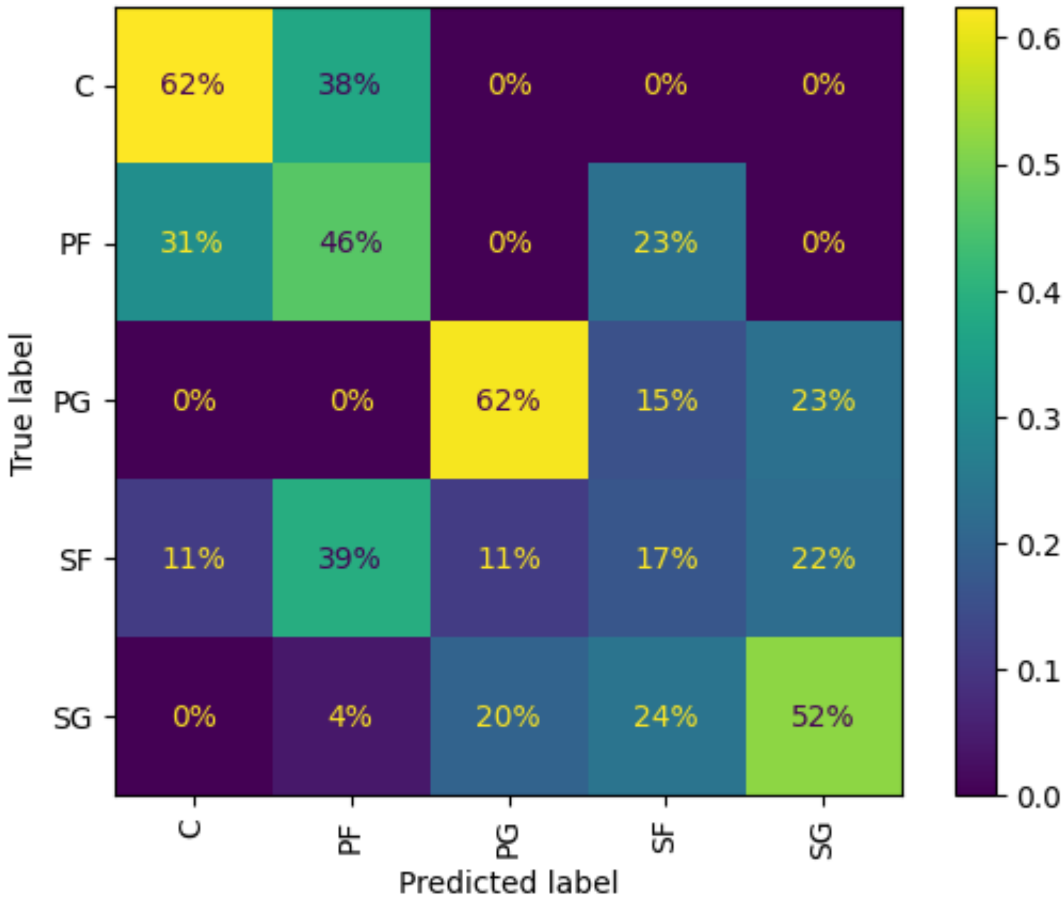
0.0


C
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True label
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Predicted label
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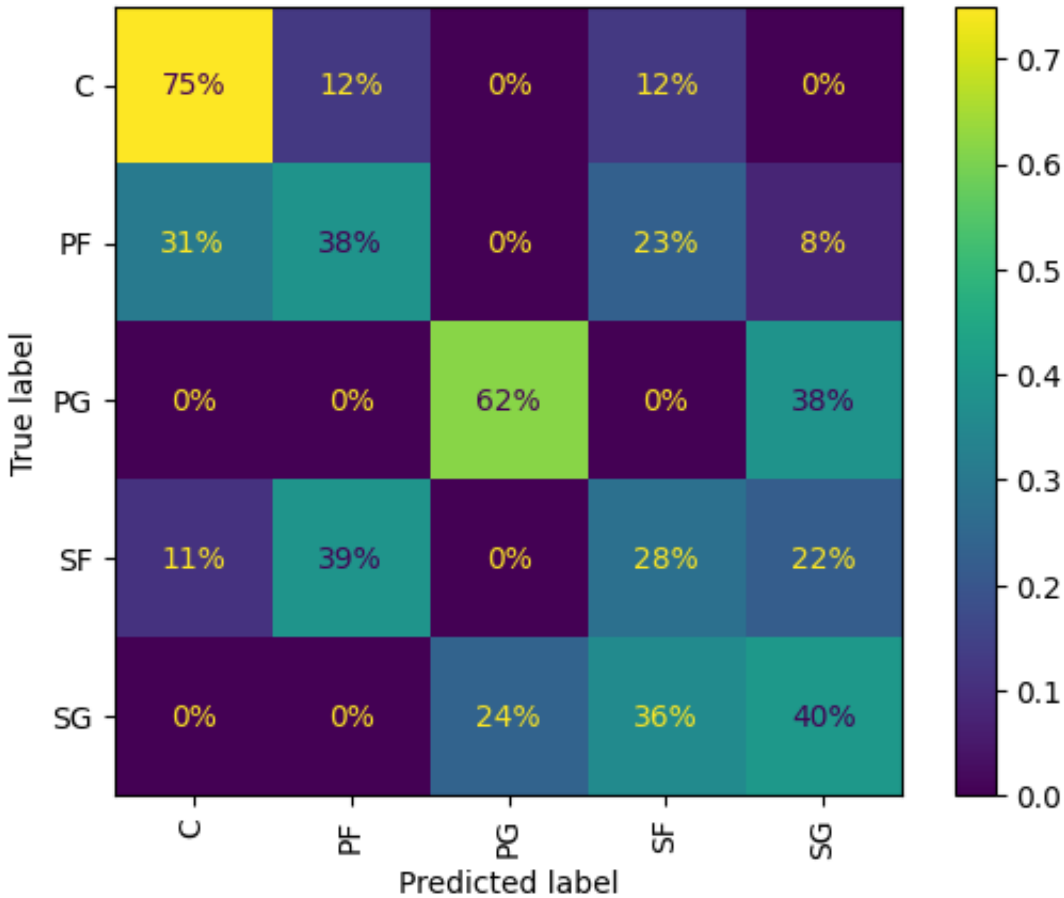
0.1
0.0


True label
Predicted label
C
PF
PG
SF
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75%
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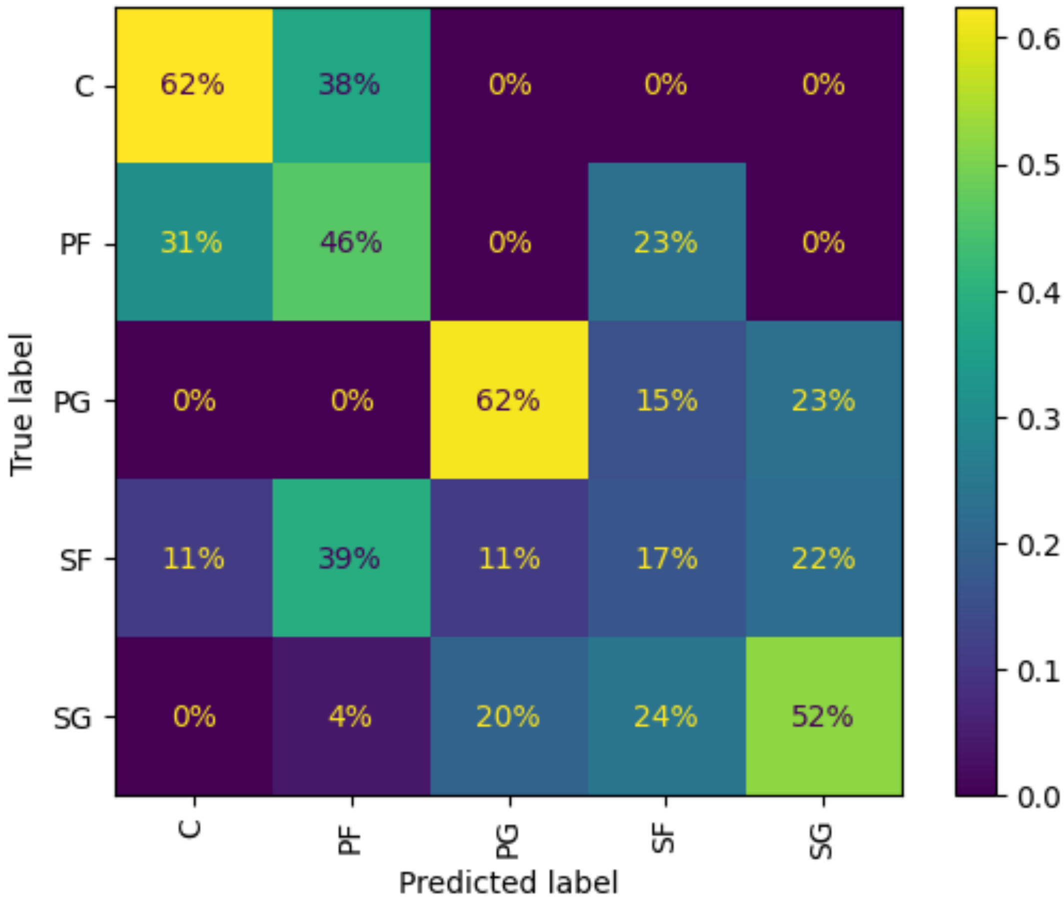

True label
Predicted label
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62%
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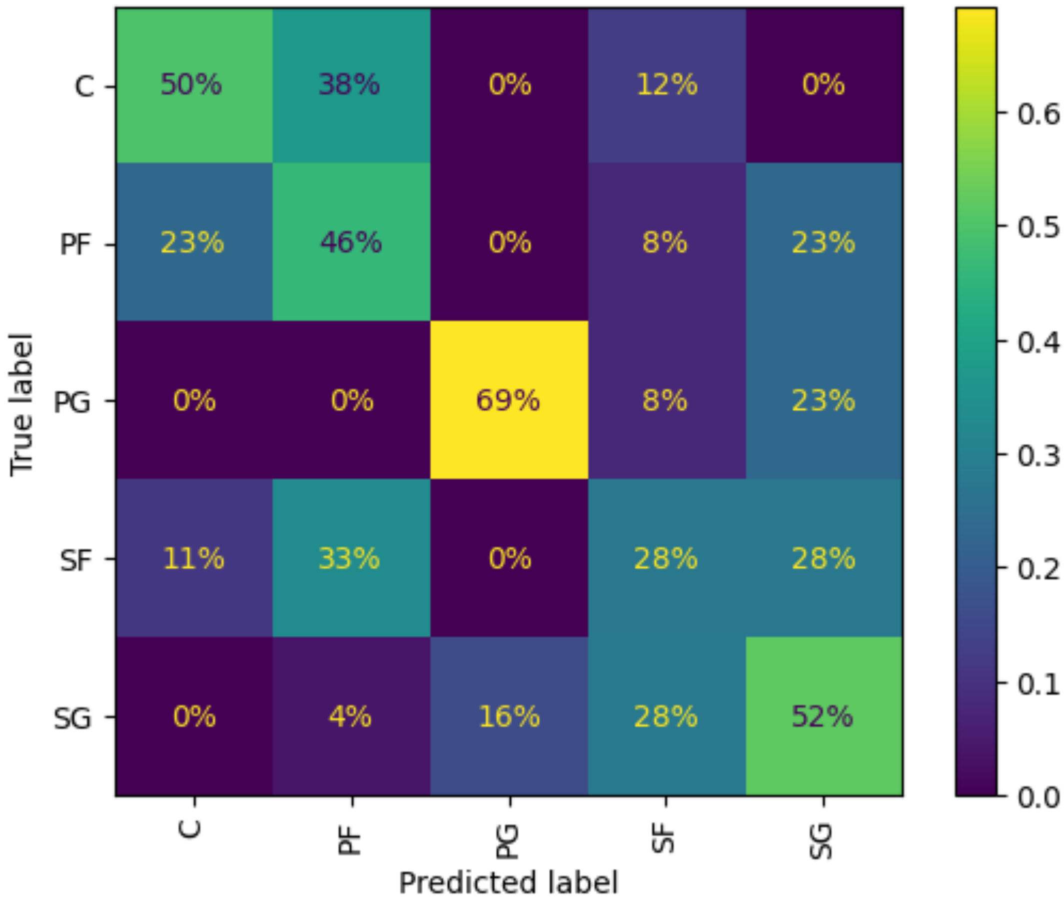
True label
Predicted label
C
PF
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SF
SG
50%
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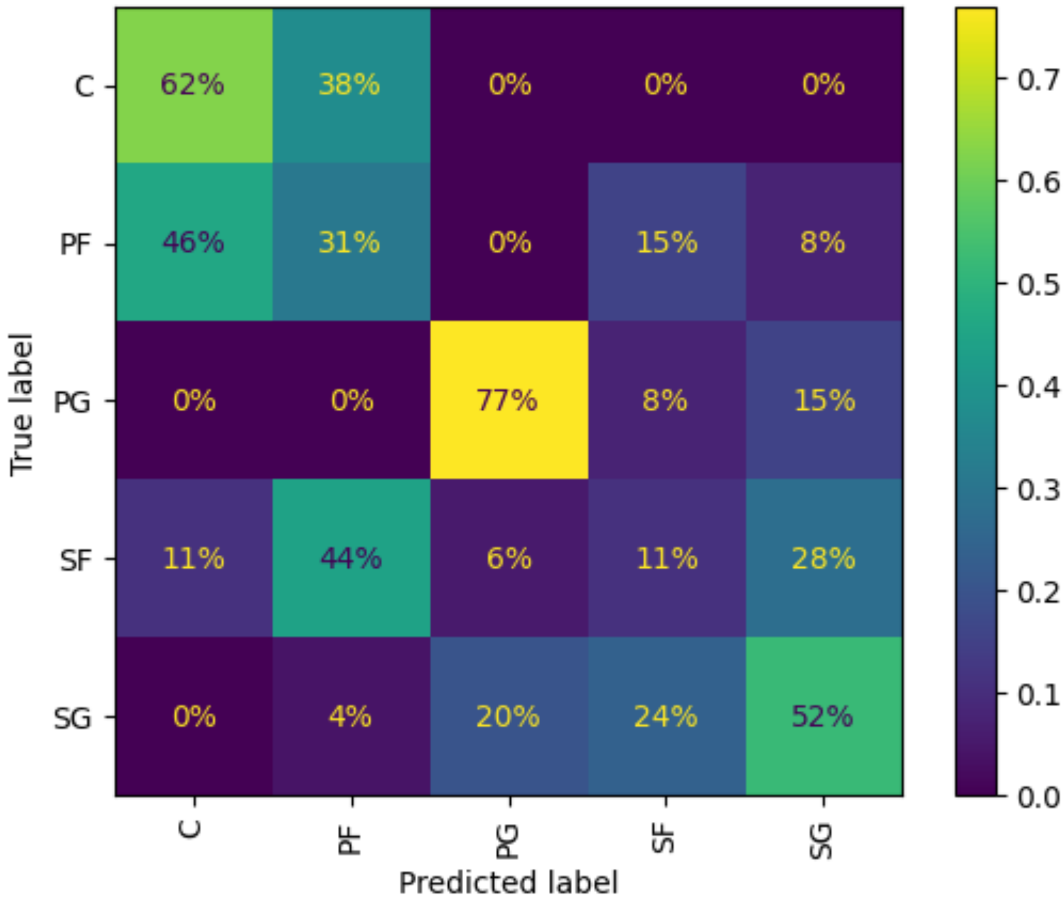
16%
28%
52%
0.6
0.5
0.4
0.3
0.2
0.1
0.0


True label
Predicted label
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SG
62%
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44%
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4%
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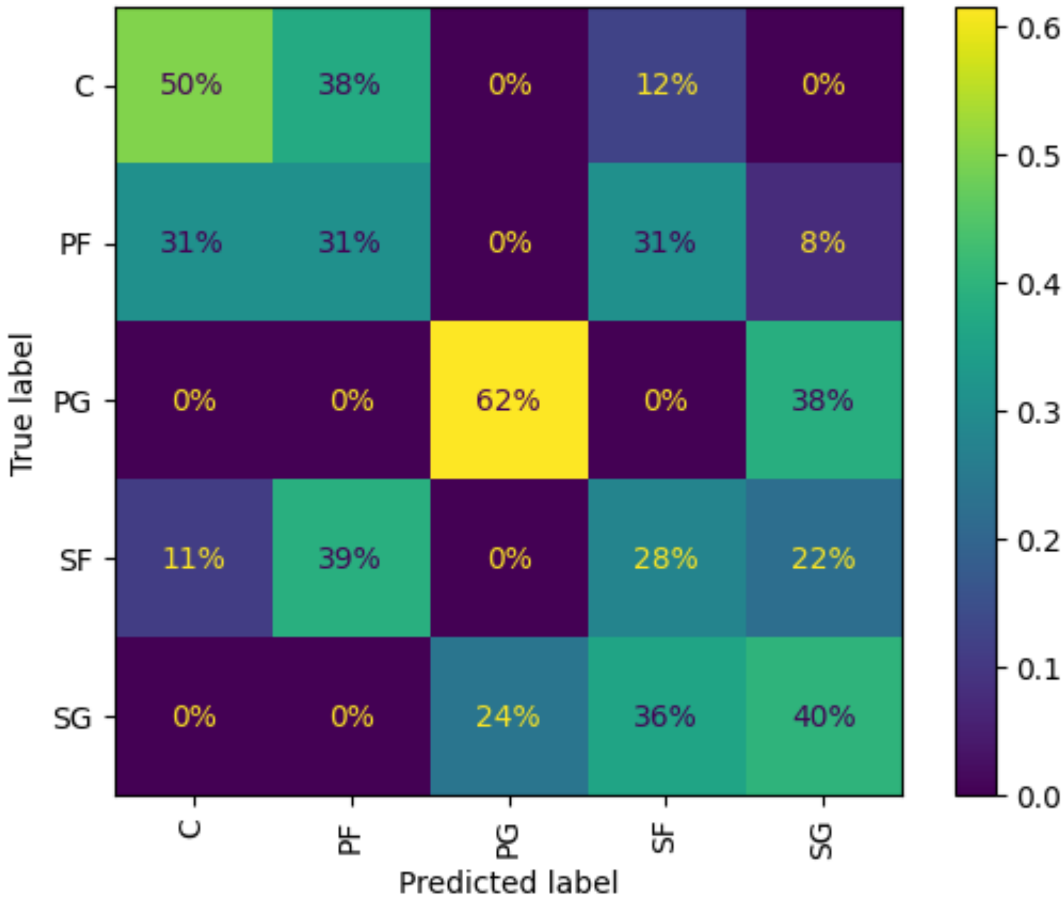
24%
52%
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0.0


C
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SG
True label
50%
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22%
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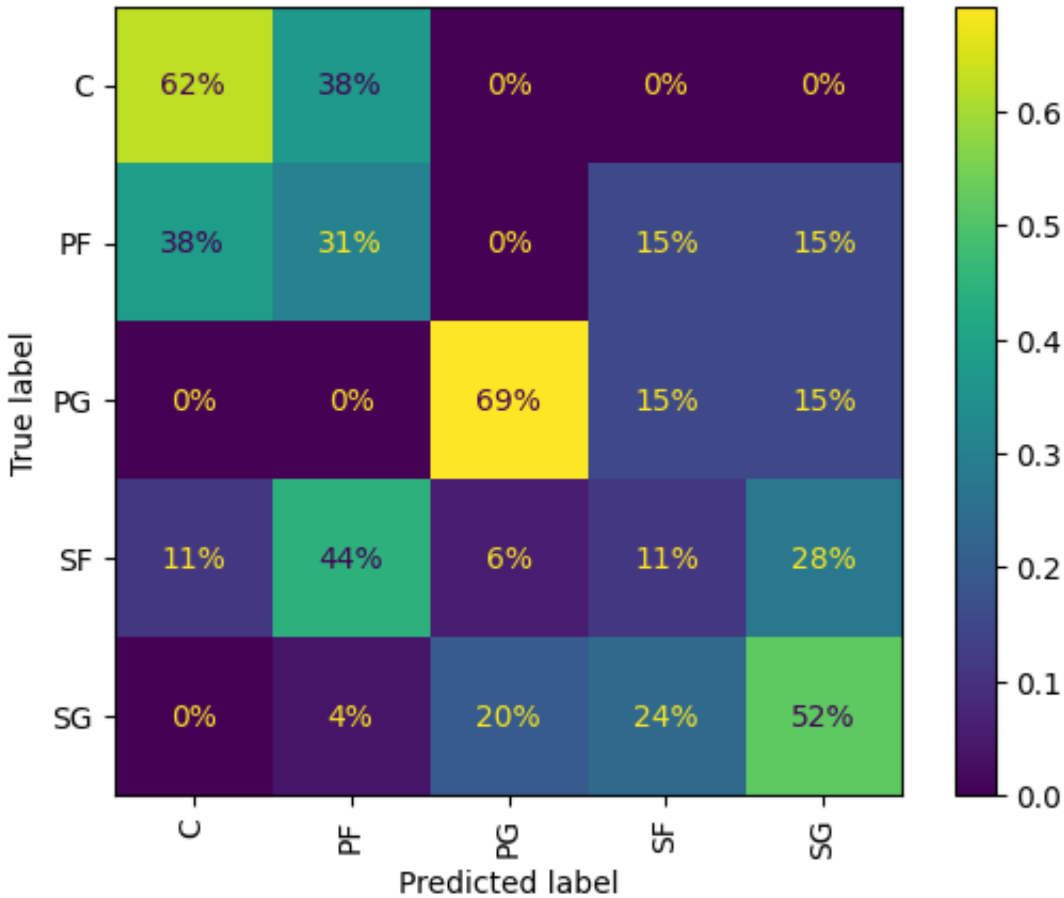
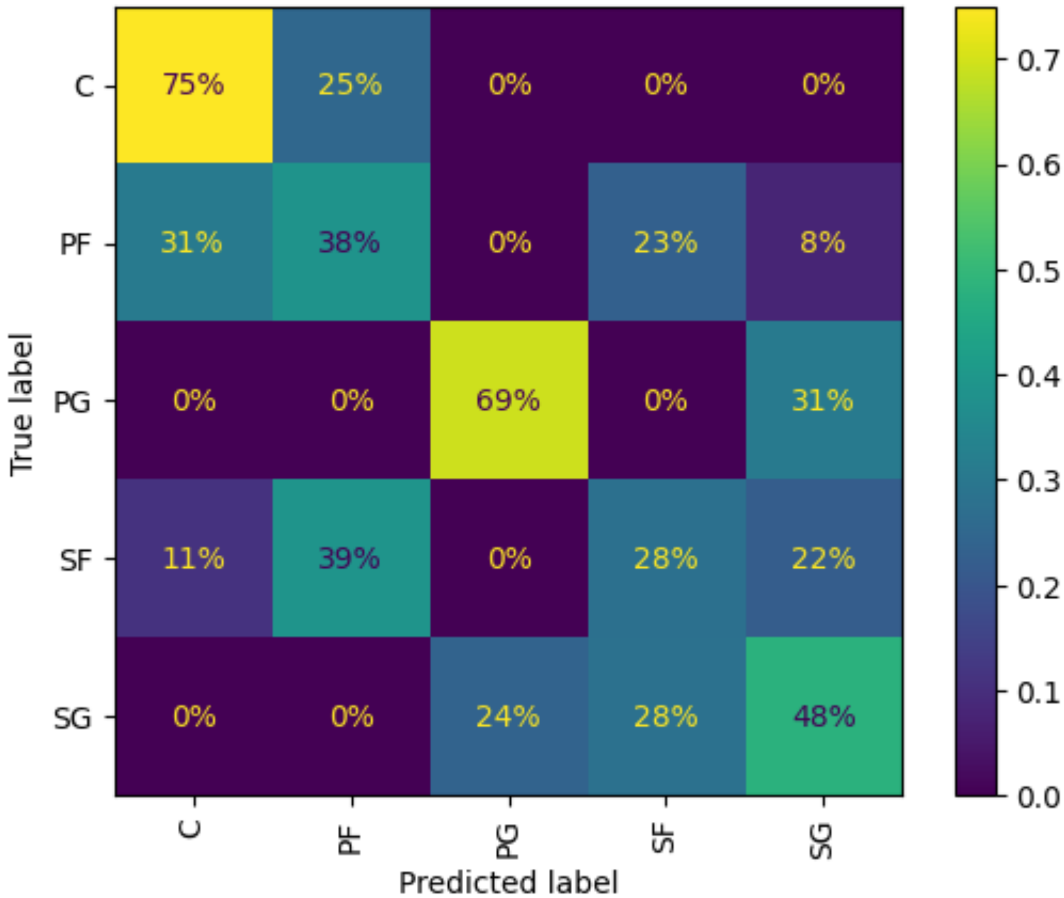
0%
24%
36%
40%
C
PF
PG
SF
SG
Predicted label
0.6
0.5
0.4
0.3
0.2
0.1
0.0

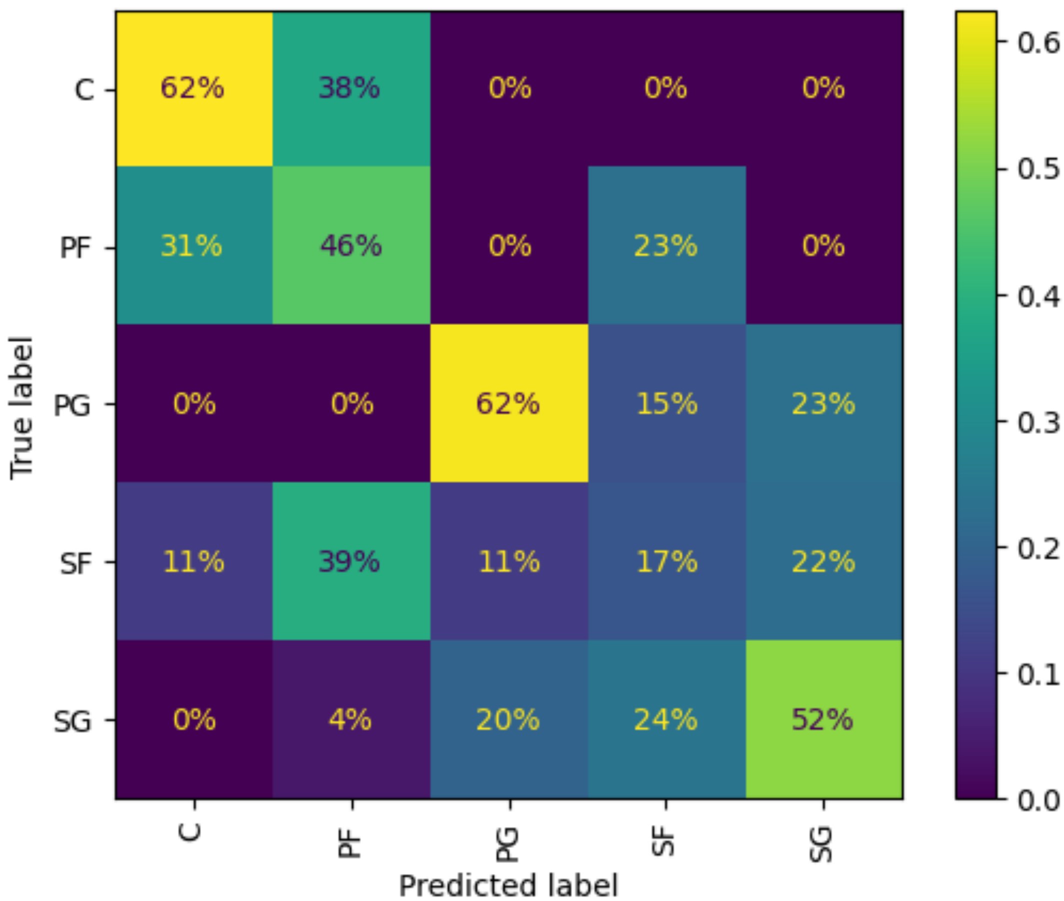

True label
Predicted label
C
PF
PG
SF
SG
62%
38%
0%
0%
0%
38%
31%
0%
15%
15%
0%
0%
69%
15%
15%
11%
44%
6%
11%
28%
0%
4%
20%
24%
52%
0.0
0.1
0.2
0.3
0.4
0.5
0.6



In [ ]:

```
# Define the SVC model with specified parameters
svc_model = SVC(C=10, degree=1, gamma=0.001, kernel='rbf', class_weight='bal

# Define the pipeline with scaler, SMOTE, and SVC
svc_pipeline = Pipeline(steps=[
    ('scaler', StandardScaler()),
    ('smote', SMOTE(random_state=42)),
    ('svc', svc_model)
])

# Fit the pipeline with the training data
svc_pipeline.fit(X_train, y_train)

# Predict using the pipeline
y_pred = svc_pipeline.predict(X_test)

# Display the confusion matrix
metrics.ConfusionMatrixDisplay.from_predictions(y_test, y_pred, normalize='t
print(metrics.classification_report(y_test, y_pred))
```

```
              precision    recall  f1-score   support

           C       0.45      0.62      0.53         8
          PF       0.35      0.46      0.40        13
          PG       0.53      0.62      0.57        13
          SF       0.21      0.17      0.19        18
          SG       0.65      0.52      0.58        25

    accuracy                           0.45        77
   macro avg       0.44      0.48      0.45        77
weighted avg       0.46      0.45      0.45        77
```



Sample test sets

In [ ]:
```
# Create a sample dataset and put it on a DataFrame
data = {
    'Assists': [4.37, 9.56, 7.59],
    'Avg_Rebound': [6.39, 2.40, 2.40],
    'TotalRebound': [2.10, 17.46, 12.42],
    'OffensiveRebound': [7.23, 0.70, 9.71],
    '2points%': [0.550, 0.364, 0.355],
```

```
    'Blocks': [0.37, 0.61, 1.05],
    'DenffesiveRebound': [4.89, 3.62, 6.51],
    'Field_goal%_squared': [0.128, 0.158, 0.173],
    'Field_goal%': [0.391, 0.457, 0.340],
    'Rolling_Points_Avg': [10.28, 11.85, 0.93],
    'TurnOver': [2, 3, 1],
    'PersonalFoul': [3, 2, 4],
    'Rolling_Assists_Max': [14, 12, 15],
    '3points%': [0.35, 0.45, 0.40],
    'Steal': [2.1, 1.8, 2.4],
    'FreeThrow%': [0.65, 0.75, 0.70],
    'Points_per_Minute': [0.50, 0.40, 0.55],
    'Points': [12, 20, 18],
    'Cross_3points_scored_assist': [5, 7, 6],
    '2points_assits': [3, 4, 6],
    'Age': [25, 22, 30],
    '3points_Assists': [4, 3, 4],
    'OffensiveRating': [107, 104, 108],
    '3points_scored': [3, 5, 7],
    'Game_Started': [6, 8, 23],
    'FreeThrow': [1.79, 1.59, 1.03],
    'Cross_2points_scored_assist': [3, 1, 8],
    'Goal_attempt': [15.94, 16.57, 6.11],
    'N_Games': [16, 35, 18],
    'FreeThrowAttempt': [4.66, 4.40, 2.80],
    'Minute_played': [12.86, 21.12, 30.07],
    'DeffensiveRating': [107, 104, 91],
    'Ratings': [21, 18, 29],
    '2points_scored': [3, 1, 5]
}

test_set = pd.DataFrame(data)
```

In [ ]:

```
# Predict labels for the new test data
y_testset_pred = svc_pipeline.predict(test_set)

print(f'Predicted Labels are: {y_testset_pred}')
```

```
Predicted Labels are: ['SG' 'PG' 'PF']
```