project

August 15, 2023

[ ]:
```
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score, classification_report
from sklearn.preprocessing import LabelEncoder
from sklearn.impute import SimpleImputer
from collections import Counter
```

[ ]:
```
# Load the Marvel dataset
marvel_url = "https://raw.githubusercontent.com/fivethirtyeight/data/master/
 ↪comic-characters/marvel-wikia-data.csv"
marvel_data = pd.read_csv(marvel_url)

# Load the DC dataset
dc_url = "https://raw.githubusercontent.com/fivethirtyeight/data/master/
 ↪comic-characters/dc-wikia-data.csv"
dc_data = pd.read_csv(dc_url)
```

[ ]:
```
def convert_first_appearance(row):
    if pd.isna(row):  # Handle NaN cases
        return row
    if type(row) == float: # Row has already been converted
        return row
    row = str(row)
    try:
        month_map = {
                        'January': 1, 'February': 2, 'March': 3, 'April': 4,
                        'May': 5, 'June': 6, 'July': 7, 'August': 8,
                        'September': 9, 'October': 10, 'November': 11,␣
 ↪'December': 12,
                        'Jan': 1, 'Feb': 2, 'Mar': 3, 'Apr': 4,
                        'May': 5, 'Jun': 6, 'Jul': 7, 'Aug': 8,
                        'Sep': 9, 'Oct': 10, 'Nov': 11, 'Dec': 12,
                        'Holiday': 11.5
                    }
        if "-" in row:  # Marvel date format (e.g., 'Sep-75')
```

```
            parts = row.split("-")
            year = int("19" + parts[1] if int(parts[1]) > 30 else "20" +␣
 ↪parts[1])
            month_abbrev = parts[0]
            month = month_map.get(month_abbrev)
        else:  # DC date format (e.g., '1999, April')
            parts = row.split(", ")
            if len(parts) == 1:
                year = int(parts[0])
                month = 1
            else:
                year = int(parts[0])
                month_abbrev = parts[1]
                month = month_map.get(month_abbrev)

        return year + (month - 1) / 12  # Normalize month to a fraction of a␣
 ↪year
    except:
        print("Error parsing date: " + row)
        raise
```

[ ]:
```
marvel_data["FIRST APPEARANCE"] = marvel_data["FIRST APPEARANCE"].
 ↪apply(convert_first_appearance)
dc_data["FIRST APPEARANCE"] = dc_data["FIRST APPEARANCE"].
 ↪apply(convert_first_appearance)
```

[ ]:
```
marvel_data.rename(columns={"Year": "YEAR"}, inplace=True)
```

[ ]:
```
# Combine datasets
combined_data = pd.concat([marvel_data, dc_data])
```

[ ]:
```
marvel_names = marvel_data["name"]
dc_names = dc_data["name"]
combined_names = combined_data["name"]
```

[ ]:
```
marvel_data = marvel_data.drop(["urlslug", "page_id", "name", "YEAR"], axis=1)
dc_data = dc_data.drop(["urlslug", "page_id", "name", "YEAR"], axis=1)
combined_data = combined_data.drop(["urlslug", "page_id", "name", "YEAR"],␣
 ↪axis=1)
```

[ ]:
```
marvel_dfs = []
for column in marvel_data.columns:
    marvel_dfs.append((column, pd.DataFrame(marvel_data[column].
 ↪value_counts(dropna=False), columns=[f"count"], index=marvel_data[column].
 ↪unique())))
```

```
for column, df in marvel_dfs:
    print(f"Column: {column}", df, sep="\n", end="\n\n")
```

```
Column: ID
                               count
Secret Identity                 6275
Public Identity                 4528
No Dual Identity                1788
Known to Authorities Identity     15
NaN                             3770

Column: ALIGN
                     count
Good Characters       4636
Neutral Characters    2208
Bad Characters        6720
NaN                   2812

Column: EYE
                   count
Hazel Eyes            76
Blue Eyes           1962
Brown Eyes          1924
Green Eyes           613
Grey Eyes             95
Yellow Eyes          256
Gold Eyes             14
Red Eyes             508
Black Eyeballs         3
Amber Eyes            10
Variable Eyes         49
NaN                 9767
Black Eyes           555
White Eyes           400
Orange Eyes           25
Silver Eyes           12
Purple Eyes           31
Pink Eyes             21
One Eye               21
Violet Eyes           11
Multiple Eyes          7
Magenta Eyes           2
Yellow Eyeballs        6
No Eyes                7
Compound Eyes          1

Column: HAIR
```

	count
Brown Hair	2339
White Hair	754
Black Hair	3755
Blond Hair	1582
No Hair	1176
Blue Hair	56
Red Hair	620
Bald	838
Auburn Hair	78
Grey Hair	531
Silver Hair	16
Purple Hair	47
Strawberry Blond Hair	47
Green Hair	117
Reddish Blond Hair	6
Gold Hair	8
NaN	4264
Orange Hair	43
Pink Hair	31
Variable Hair	32
Yellow Hair	20
Light Brown Hair	6
Magenta Hair	5
Bronze Hair	1
Dyed Hair	1
Orange-brown Hair	3

Column: SEX

	count
Male Characters	11638
Female Characters	3837
Genderfluid Characters	2
Agender Characters	45
NaN	854

Column: GSM

	count
NaN	16286
Bisexual Characters	19
Transvestites	1
Homosexual Characters	66
Pansexual Characters	1
Transgender Characters	2
Genderfluid Characters	1

Column: ALIVE

	count

```
Living Characters    12608
Deceased Characters   3765
NaN                      3

Column: APPEARANCES
        count
4043.0      1
3360.0      1
3061.0      1
2961.0      1
2258.0      1
…           …
4.0      1097
3.0      1419
2.0      2074
1.0      4810
NaN      1096

[359 rows x 1 columns]

Column: FIRST APPEARANCE
              count
1962.583333      19
1941.166667      53
1974.750000      18
1963.166667      16
1950.833333      12
…                …
1957.250000       2
1957.083333       1
1959.666667       1
1962.416667       4
1956.166667       1

[833 rows x 1 columns]
```

[ ]:
```
dc_dfs = []
for column in dc_data.columns:
    dc_dfs.append((column, pd.DataFrame(dc_data[column].
 ↪value_counts(dropna=False), columns=[f"count"], index=dc_data[column].
 ↪unique())))
for column, df in dc_dfs:
    print(f"Column: {column}", df, sep="\n", end="\n\n")
```

```
Column: ID
                  count
Secret Identity    2408
```

Public Identity	2466
NaN	2013
Identity Unknown	9

Column: ALIGN

	count
Good Characters	2832
Bad Characters	2895
Neutral Characters	565
NaN	601
Reformed Criminals	3

Column: EYE

	count
Blue Eyes	1102
Brown Eyes	879
Green Eyes	291
Purple Eyes	14
Black Eyes	412
White Eyes	116
Red Eyes	208
Photocellular Eyes	48
Hazel Eyes	23
Amber Eyes	5
Yellow Eyes	86
NaN	3628
Grey Eyes	40
Pink Eyes	6
Violet Eyes	12
Gold Eyes	9
Orange Eyes	10
Auburn Hair	7

Column: HAIR

	count
Black Hair	1574
Brown Hair	1148
White Hair	346
Blond Hair	744
Red Hair	461
NaN	2274
Green Hair	42
Strawberry Blond Hair	28
Grey Hair	157
Silver Hair	3
Orange Hair	21
Purple Hair	32
Gold Hair	5

```
Blue Hair                 41
Reddish Brown Hair         3
Pink Hair                 11
Violet Hair                4
Platinum Blond Hair        2
```

```
Column: SEX
                        count
Male Characters          4783
Female Characters        1967
NaN                       125
Genderless Characters      20
Transgender Characters      1
```

```
Column: GSM
                       count
NaN                     6832
Bisexual Characters       10
Homosexual Characters     54
```

```
Column: ALIVE
                     count
Living Characters     5200
Deceased Characters   1693
NaN                      3
```

```
Column: APPEARANCES
        count
3093.0      1
2496.0      1
1565.0      1
1316.0      1
1237.0      1
…       …
4.0       499
3.0       506
2.0       709
1.0      1002
NaN       355

[283 rows x 1 columns]
```

```
Column: FIRST APPEARANCE
             count
1939.333333      1
1986.750000     17
1959.750000      5
1987.083333     29
```

```
1940.250000      4
…                …
1946.583333      1
2012.333333      1
1975.166667      1
1974.083333      1
1946.250000      1

[755 rows x 1 columns]
```

[ ]:
```python
combined_dfs = []
for column in combined_data.columns:
    combined_dfs.append((column, pd.DataFrame(combined_data[column].
 ↪value_counts(dropna=False), columns=[f"count"], index=combined_data[column].
 ↪unique())))
for column, df in combined_dfs:
    print(f"Column: {column}", df, sep="\n", end="\n\n")
```

```
Column: ID
                               count
Secret Identity                 8683
Public Identity                 6994
No Dual Identity                1788
Known to Authorities Identity     15
NaN                             5783
Identity Unknown                   9

Column: ALIGN
                     count
Good Characters       7468
Neutral Characters    2773
Bad Characters        9615
NaN                   3413
Reformed Criminals       3

Column: EYE
                     count
Hazel Eyes              99
Blue Eyes             3064
Brown Eyes            2803
Green Eyes             904
Grey Eyes              135
Yellow Eyes            342
Gold Eyes               23
Red Eyes               716
Black Eyeballs           3
Amber Eyes              15
```

Variable Eyes	49
NaN	13395
Black Eyes	967
White Eyes	516
Orange Eyes	35
Silver Eyes	12
Purple Eyes	45
Pink Eyes	27
One Eye	21
Violet Eyes	23
Multiple Eyes	7
Magenta Eyes	2
Yellow Eyeballs	6
No Eyes	7
Compound Eyes	1
Photocellular Eyes	48
Auburn Hair	7

Column: HAIR

	count
Brown Hair	3487
White Hair	1100
Black Hair	5329
Blond Hair	2326
No Hair	1176
Blue Hair	97
Red Hair	1081
Bald	838
Auburn Hair	78
Grey Hair	688
Silver Hair	19
Purple Hair	79
Strawberry Blond Hair	75
Green Hair	159
Reddish Blond Hair	6
Gold Hair	13
NaN	6538
Orange Hair	64
Pink Hair	42
Variable Hair	32
Yellow Hair	20
Light Brown Hair	6
Magenta Hair	5
Bronze Hair	1
Dyed Hair	1
Orange-brown Hair	3
Reddish Brown Hair	3
Violet Hair	4

```
Platinum Blond Hair        2

Column: SEX
                         count
Male Characters          16421
Female Characters         5804
Genderfluid Characters       2
Agender Characters          45
NaN                        979
Genderless Characters       20
Transgender Characters       1

Column: GSM
                         count
NaN                      23118
Bisexual Characters         29
Transvestites                1
Homosexual Characters      120
Pansexual Characters         1
Transgender Characters       2
Genderfluid Characters       1

Column: ALIVE
                      count
Living Characters     17808
Deceased Characters    5458
NaN                       6

Column: APPEARANCES
        count
4043.0      1
3360.0      1
3061.0      1
2961.0      1
2258.0      1
…       …
167.0       1
162.0       1
159.0       1
154.0       1
123.0       3

[443 rows x 1 columns]

Column: FIRST APPEARANCE
             count
1962.583333     21
1941.166667     53
```

```
1974.750000     20
1963.166667     16
1950.833333     12
…               …
1958.166667      4
1936.666667      1
1988.875000      2
1949.916667      2
2013.750000      1

[881 rows x 1 columns]
```

[ ]:
```
# List of target features (exclude "url", "page_id", and "name")
target_features = ["ALIGN", "SEX", "EYE", "HAIR", "GSM", "ALIVE", "ID"]
```

[ ]:
```
rf_models_marvel = []
rf_models_dc = []
rf_models_combined = []
```

[ ]:
```
for target_feature in target_features:
    #print(f"""Target feature: {target_feature}""")

    # Create dataset with target_feature as the target column for each category
    data_marvel = marvel_data.dropna(subset=[target_feature])
    data_dc = dc_data.dropna(subset=[target_feature])
    data_combined = combined_data.dropna(subset=[target_feature])

    features_marvel = data_marvel.drop(target_feature, axis=1)
    features_dc = data_dc.drop(target_feature, axis=1)
    features_combined = data_combined.drop(target_feature, axis=1)

    targets_marvel = data_marvel[target_feature]
    targets_dc = data_dc[target_feature]
    targets_combined = data_combined[target_feature]

    classes = targets_marvel.unique()

    # Encode target feature
    le_marvel = LabelEncoder()
    le_dc = LabelEncoder()
    le_combined = LabelEncoder()
    y_marvel = le_marvel.fit_transform(targets_marvel)
    y_dc = le_dc.fit_transform(targets_dc)
    y_combined = le_combined.fit_transform(targets_combined)

    # One-hot encode features
```

```
    columns = [tf for tf in target_features if tf != target_feature]
    onehot_features_marvel = pd.get_dummies(features_marvel, columns=columns)
    onehot_features_dc = pd.get_dummies(features_dc, columns=columns)
    onehot_features_combined = pd.get_dummies(features_combined,␣
↪columns=columns)

    # Impute missing values
    imputer = SimpleImputer(strategy="mean")
    imputed_onehot_features_marvel = imputer.
↪fit_transform(onehot_features_marvel)
    imputed_onehot_features_dc = imputer.fit_transform(onehot_features_dc)
    imputed_onehot_features_combined = imputer.
↪fit_transform(onehot_features_combined)

    # Final features dataframe
    X_marvel = pd.DataFrame(imputed_onehot_features_marvel,␣
↪columns=onehot_features_marvel.columns)
    X_dc = pd.DataFrame(imputed_onehot_features_dc, columns=onehot_features_dc.
↪columns)
    X_combined = pd.DataFrame(imputed_onehot_features_combined,␣
↪columns=onehot_features_combined.columns)

    # Split data into training and testing sets

    X_train_marvel, X_test_marvel, y_train_marvel, y_test_marvel =␣
↪train_test_split(X_marvel, y_marvel, test_size=0.2, random_state=42)
    X_train_dc, X_test_dc, y_train_dc, y_test_dc = train_test_split(X_dc, y_dc,␣
↪test_size=0.2, random_state=42)
    X_train_combined, X_test_combined, y_train_combined, y_test_combined =␣
↪train_test_split(X_combined, y_combined, test_size=0.2, random_state=42)

    # Create RandomForest classifiers for each category
    rf_classifier_marvel = RandomForestClassifier(n_estimators=100,␣
↪random_state=42)
    rf_classifier_dc = RandomForestClassifier(n_estimators=100, random_state=42)
    rf_classifier_combined = RandomForestClassifier(n_estimators=100,␣
↪random_state=42)

    # Get the unique class labels from the original target data
    marvel_unique_class_labels = np.unique(y_marvel)
    print(marvel_unique_class_labels)
    dc_unique_class_labels = np.unique(y_dc)
    combined_unique_class_labels = np.unique(y_combined)

    # Convert the unique class labels to a list
    marvel_class_names = le_marvel.inverse_transform(marvel_unique_class_labels)
```

```
    print(marvel_class_names)
    dc_class_names = le_dc.inverse_transform(dc_unique_class_labels)
    combined_class_names = le_combined.
 ↪inverse_transform(combined_unique_class_labels)

    # Store the trained models in the respective lists
    rf_models_marvel.append((rf_classifier_marvel, X_train_marvel,␣
 ↪y_train_marvel, X_test_marvel, y_test_marvel, target_feature,␣
 ↪marvel_class_names))
    rf_models_dc.append((rf_classifier_dc, X_train_dc, y_train_dc, X_test_dc,␣
 ↪y_test_dc, target_feature, dc_class_names))
    rf_models_combined.append((rf_classifier_combined, X_train_combined,␣
 ↪y_train_combined, X_test_combined, y_test_combined, target_feature,␣
 ↪combined_class_names))
```

```
[0 1 2]
['Bad Characters' 'Good Characters' 'Neutral Characters']
[0 1 2 3]
['Agender Characters' 'Female Characters' 'Genderfluid Characters'
 'Male Characters']
[ 0  1  2  3  4  5  6  7  8  9 10 11 12 13 14 15 16 17 18 19 20 21 22 23]
['Amber Eyes' 'Black Eyeballs' 'Black Eyes' 'Blue Eyes' 'Brown Eyes'
 'Compound Eyes' 'Gold Eyes' 'Green Eyes' 'Grey Eyes' 'Hazel Eyes'
 'Magenta Eyes' 'Multiple Eyes' 'No Eyes' 'One Eye' 'Orange Eyes'
 'Pink Eyes' 'Purple Eyes' 'Red Eyes' 'Silver Eyes' 'Variable Eyes'
 'Violet Eyes' 'White Eyes' 'Yellow Eyeballs' 'Yellow Eyes']
[ 0  1  2  3  4  5  6  7  8  9 10 11 12 13 14 15 16 17 18 19 20 21 22 23
 24]
['Auburn Hair' 'Bald' 'Black Hair' 'Blond Hair' 'Blue Hair' 'Bronze Hair'
 'Brown Hair' 'Dyed Hair' 'Gold Hair' 'Green Hair' 'Grey Hair'
 'Light Brown Hair' 'Magenta Hair' 'No Hair' 'Orange Hair'
 'Orange-brown Hair' 'Pink Hair' 'Purple Hair' 'Red Hair'
 'Reddish Blond Hair' 'Silver Hair' 'Strawberry Blond Hair'
 'Variable Hair' 'White Hair' 'Yellow Hair']
[0 1 2 3 4 5]
['Bisexual Characters' 'Genderfluid Characters' 'Homosexual Characters'
 'Pansexual Characters' 'Transgender Characters' 'Transvestites']
[0 1]
['Deceased Characters' 'Living Characters']
[0 1 2 3]
['Known to Authorities Identity' 'No Dual Identity' 'Public Identity'
 'Secret Identity']
```

[ ]:
```
for rf_model, X_train, y_train, X_test, y_test, target_feature, _ in␣
 ↪rf_models_marvel:
    try:
        rf_model.fit(X_train, y_train)
```

```
        y_pred = rf_model.predict(X_test)
        print(f"""Accuracy score for Marvel {target_feature} predictions:␣
↪{accuracy_score(y_test, y_pred)}""")
    except:
        print(f"""Not enough data for Marvel {target_feature} predictions""")
        continue
```

```
Accuracy score for Marvel ALIGN predictions: 0.5576852193144121
Accuracy score for Marvel SEX predictions: 0.7314009661835749
Accuracy score for Marvel EYE predictions: 0.4122541603630862
Accuracy score for Marvel HAIR predictions: 0.3033429632686752
Accuracy score for Marvel GSM predictions: 0.8333333333333334
Accuracy score for Marvel ALIVE predictions: 0.7312977099236642
Accuracy score for Marvel ID predictions: 0.5452022204599524
```

[ ]:
```
for rf_model, X_train, y_train, X_test, y_test, target_feature, _ in␣
↪rf_models_dc:
    try:
        rf_model.fit(X_train, y_train)
        y_pred = rf_model.predict(X_test)
        print(f"""Accuracy score for DC {target_feature} predictions:␣
↪{accuracy_score(y_test, y_pred)}""")
    except:
        print(f"""Not enough data for DC {target_feature} predictions""")
        continue
```

```
Accuracy score for DC ALIGN predictions: 0.5972994440031771
Accuracy score for DC SEX predictions: 0.6937269372693727
Accuracy score for DC EYE predictions: 0.42813455657492355
Accuracy score for DC HAIR predictions: 0.2972972972972973
Accuracy score for DC GSM predictions: 0.8461538461538461
Accuracy score for DC ALIVE predictions: 0.7251631617113851
Accuracy score for DC ID predictions: 0.6264073694984647
```

[ ]:
```
for rf_model, X_train, y_train, X_test, y_test, target_feature, _ in␣
↪rf_models_combined:
    try:
        rf_model.fit(X_train, y_train)
        y_pred = rf_model.predict(X_test)
        print(f"""Accuracy score for combined {target_feature} predictions:␣
↪{accuracy_score(y_test, y_pred)}""")
    except:
        print(f"""Not enough data for combined {target_feature} predictions""")
        continue
```

```
Accuracy score for combined ALIGN predictions: 0.5662134944612286
Accuracy score for combined SEX predictions: 0.7151827764072662
```

```
Accuracy score for combined EYE predictions: 0.40384615384615385
Accuracy score for combined HAIR predictions: 0.2954884971616373
Accuracy score for combined GSM predictions: 0.7741935483870968
Accuracy score for combined ALIVE predictions: 0.7367855608079071
Accuracy score for combined ID predictions: 0.5465980560320183
```

[ ]:
```
import shap

shap.initjs()
```

```
Using `tqdm.autonotebook.tqdm` in notebook mode. Use `tqdm.tqdm` instead to
force console mode (e.g. in jupyter console)
```

```
<IPython.core.display.HTML object>
```

[ ]:
```
shap_models_marvel = []

for rf_model, X_train, y_train, X_test, y_test, target_feature, class_names in␣
 ↪rf_models_marvel:
    print(f"""Creating SHAP values for Marvel {target_feature} predictions with␣
 ↪{len(X_test)} samples""")
    subset_size = min((int(len(X_test) * 0.1) if len(X_test) > 250 else␣
 ↪len(X_test)), 10)
    print(f"""Subset size: {subset_size}""")

    explainer = shap.TreeExplainer(rf_model)
    shap_values = explainer.shap_values(X_test[:subset_size])
    shap_models_marvel.append((explainer, shap_values, X_test[:subset_size],␣
 ↪target_feature, class_names))
    print(f"""SHAP values for Marvel {target_feature} predictions created""")

print("Marvel SHAP values created")
```

```
Creating SHAP values for Marvel ALIGN predictions with 2713 samples
Subset size: 10
SHAP values for Marvel ALIGN predictions created
Creating SHAP values for Marvel SEX predictions with 3105 samples
Subset size: 10
SHAP values for Marvel SEX predictions created
Creating SHAP values for Marvel EYE predictions with 1322 samples
Subset size: 10
SHAP values for Marvel EYE predictions created
Creating SHAP values for Marvel HAIR predictions with 2423 samples
Subset size: 10
SHAP values for Marvel HAIR predictions created
Creating SHAP values for Marvel GSM predictions with 18 samples
Subset size: 10
SHAP values for Marvel GSM predictions created
```

```
Creating SHAP values for Marvel ALIVE predictions with 3275 samples
Subset size: 10
SHAP values for Marvel ALIVE predictions created
Creating SHAP values for Marvel ID predictions with 2522 samples
Subset size: 10
SHAP values for Marvel ID predictions created
Marvel SHAP values created
```

[ ]:
```
# Create SHAP values for DC

shap_models_dc = []

for rf_model, X_train, y_train, X_test, y_test, target_feature, class_names in␣
 ↪rf_models_dc:
    print(f"""Creating SHAP values for DC {target_feature} predictions with␣
 ↪{len(X_test)} samples""")
    subset_size = min((int(len(X_test) * 0.1) if len(X_test) > 250 else␣
 ↪len(X_test)), 10)
    print(f"""Subset size: {subset_size}""")

    explainer = shap.TreeExplainer(rf_model)
    shap_values = explainer.shap_values(X_test[:subset_size])
    shap_models_dc.append((explainer, shap_values, X_test[:subset_size],␣
 ↪target_feature, class_names))
    print(f"""SHAP values for DC {target_feature} predictions created""")

print("DC SHAP values created")
```

```
Creating SHAP values for DC ALIGN predictions with 1259 samples
Subset size: 10
SHAP values for DC ALIGN predictions createdSHAP values for DC ALIGN predictions
created
Creating SHAP values for DC SEX predictions with 1355 samples
Subset size: 10
SHAP values for DC SEX predictions created
Creating SHAP values for DC EYE predictions with 654 samples
Subset size: 10
SHAP values for DC EYE predictions created
Creating SHAP values for DC HAIR predictions with 925 samples
Subset size: 10
SHAP values for DC HAIR predictions created
Creating SHAP values for DC GSM predictions with 13 samples
Subset size: 10
SHAP values for DC GSM predictions created
Creating SHAP values for DC ALIVE predictions with 1379 samples
Subset size: 10
SHAP values for DC ALIVE predictions created
```

```
Creating SHAP values for DC ID predictions with 977 samples
Subset size: 10
SHAP values for DC ID predictions created
DC SHAP values created
```

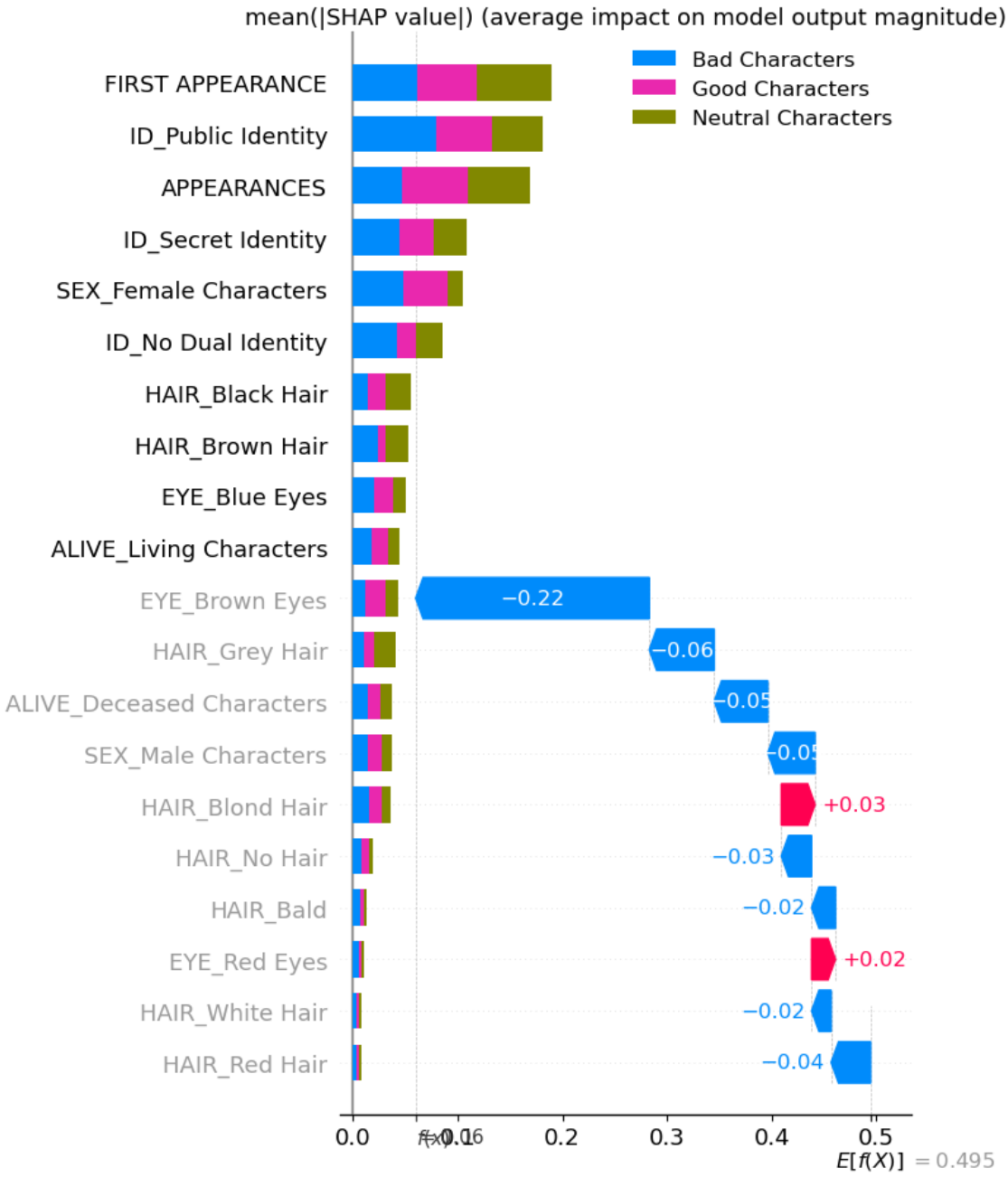
[ ]:
```python
# Create SHAP values for combined

shap_models_combined = []

for rf_model, X_train, y_train, X_test, y_test, target_feature, class_names in␣
 ↪rf_models_combined:
    print(f"""Creating SHAP values for combined {target_feature} predictions␣
 ↪with {len(X_test)} samples""")
    subset_size = min((int(len(X_test) * 0.1) if len(X_test) > 250 else␣
 ↪len(X_test)), 10)
    print(f"""Subset size: {subset_size}""")

    explainer = shap.TreeExplainer(rf_model)
    shap_values = explainer.shap_values(X_test[:subset_size])
    shap_models_combined.append((explainer, shap_values, X_test[:subset_size],␣
 ↪target_feature, class_names))
    print(f"""SHAP values for combined {target_feature} predictions created""")

print("Combined SHAP values created")
```

```
Creating SHAP values for combined ALIGN predictions with 3972 samples
Subset size: 10
SHAP values for combined ALIGN predictions created
Creating SHAP values for combined SEX predictions with 4459 samples
Subset size: 10
SHAP values for combined SEX predictions created
Creating SHAP values for combined EYE predictions with 1976 samples
Subset size: 10
SHAP values for combined EYE predictions created
Creating SHAP values for combined HAIR predictions with 3347 samples
Subset size: 10
SHAP values for combined HAIR predictions created
Creating SHAP values for combined GSM predictions with 31 samples
Subset size: 10
SHAP values for combined GSM predictions created
Creating SHAP values for combined ALIVE predictions with 4654 samples
Subset size: 10
SHAP values for combined ALIVE predictions created
Creating SHAP values for combined ID predictions with 3498 samples
Subset size: 10
SHAP values for combined ID predictions created
Combined SHAP values created
```

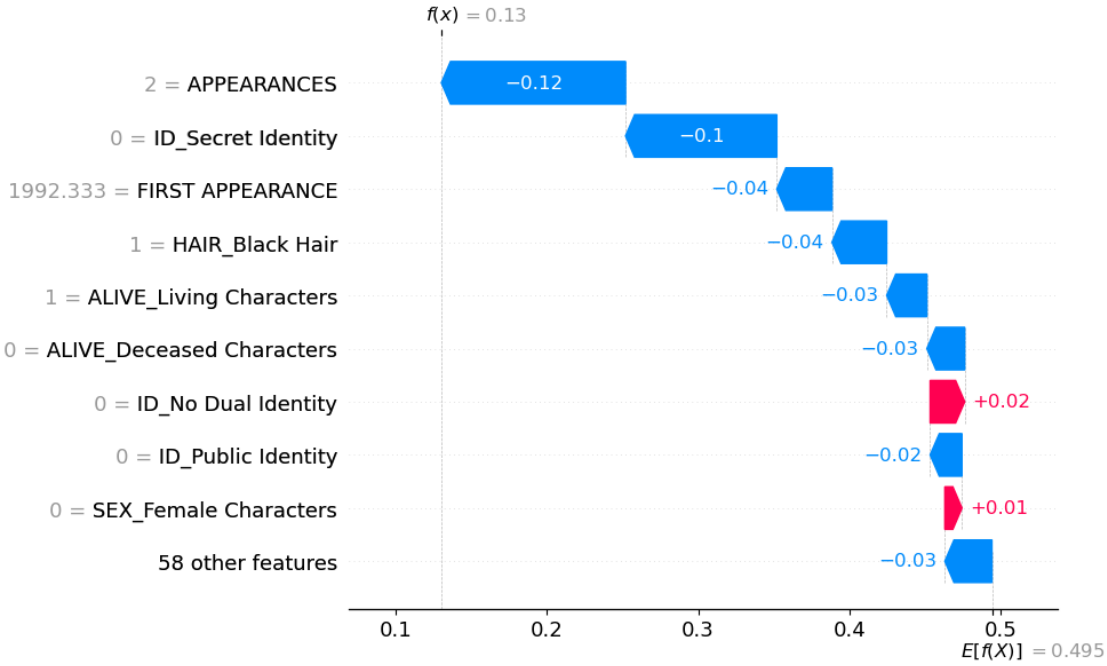
[ ]:
```
import random
import matplotlib.pyplot as plt
```

[ ]:
```
# Create plots for Marvel

for explainer, shap_values, feature_subset, target_feature, class_names in␣
 ↪shap_models_marvel:
    num_samples = len(feature_subset)
    sample_index = random.randint(0, num_samples - 1)  # Generate a random␣
 ↪index within the valid range

    print(f"Creating Summary plot for Marvel {target_feature} predictions")
    shap.summary_plot(shap_values, feature_subset, feature_names=feature_subset.
 ↪columns, show=False, class_names=class_names)
    plt.savefig(f"figs/summary/Marvel_{target_feature}_summary.png")
    plt.show()
    print(f"Created Summary plot for Marvel {target_feature} predictions")

    print(f"Creating Waterfall plot for Marvel {target_feature} predictions")
    shap.plots.waterfall(shap.Explanation(values=shap_values[0][sample_index],␣
 ↪base_values=explainer.expected_value[0], data=feature_subset.
 ↪iloc[sample_index]), max_display=10, show=False)
    plt.savefig(f"figs/waterfall/
 ↪Marvel_{target_feature}_{sample_index}_waterfall.png")
    plt.show()
    print(f"Created Waterfall plot for Marvel {target_feature} predictions")


print("Marvel plots created")
```

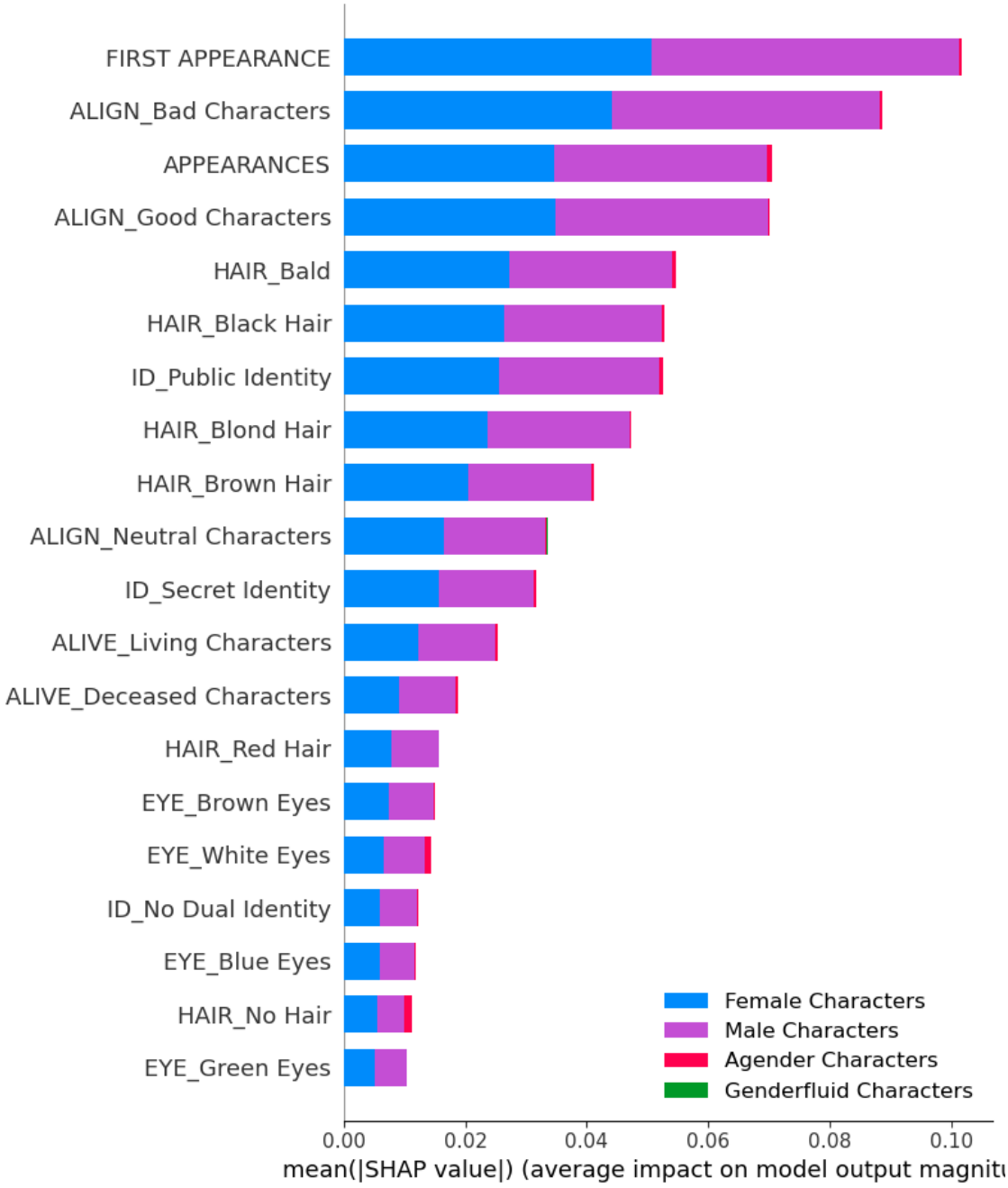
```
Creating Summary plot for Marvel ALIGN predictions
```



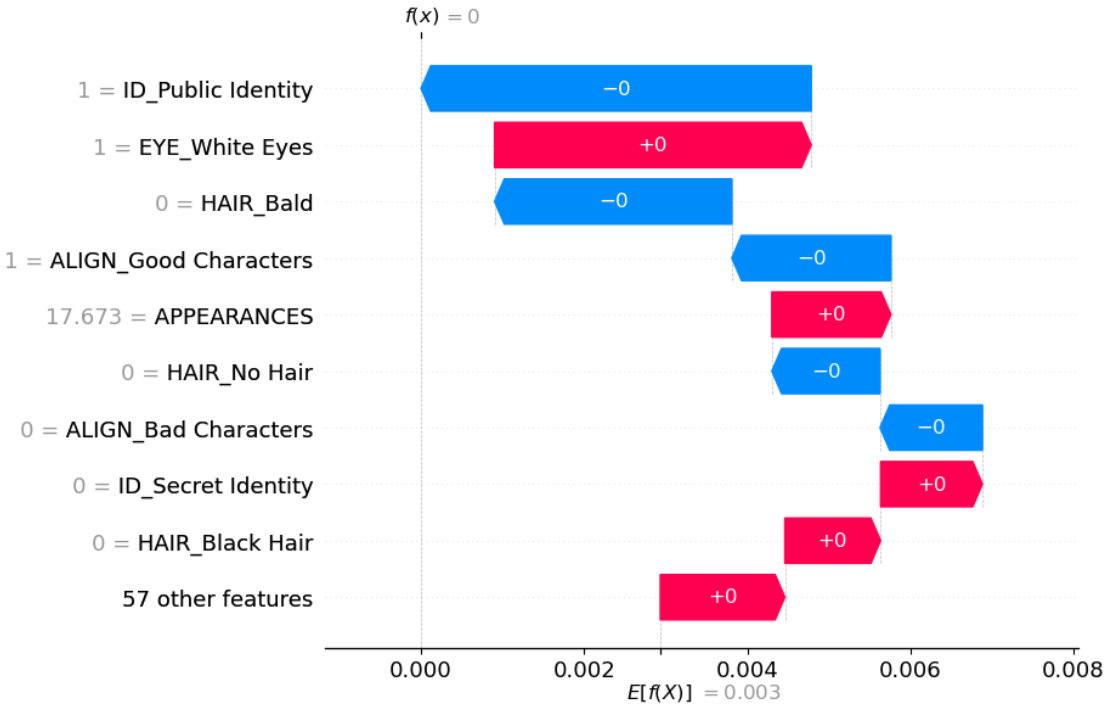

```
Created Summary plot for Marvel ALIGN predictions
Creating Waterfall plot for Marvel ALIGN predictions
```



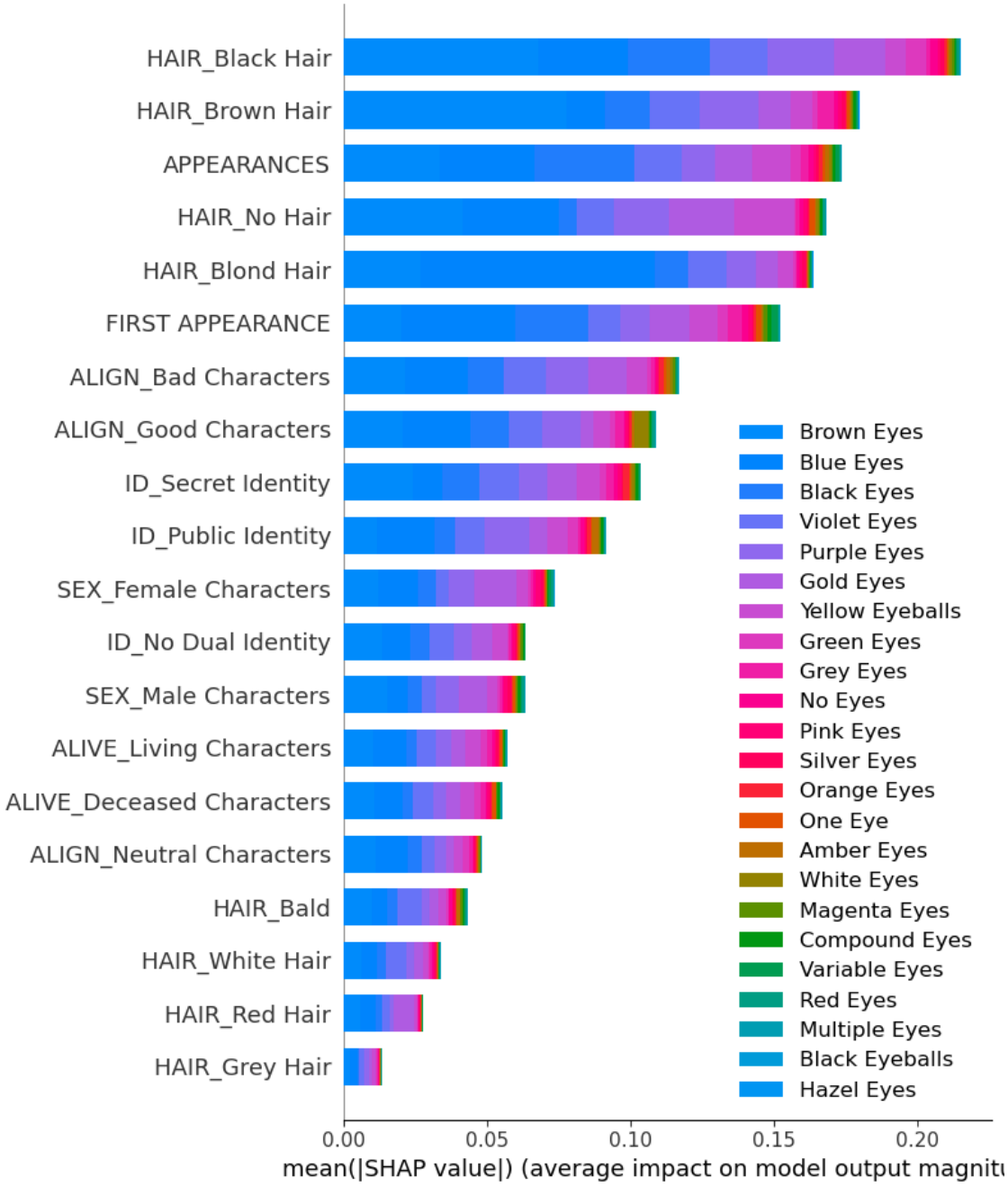

```
Created Waterfall plot for Marvel ALIGN predictions
Creating Summary plot for Marvel SEX predictions
```



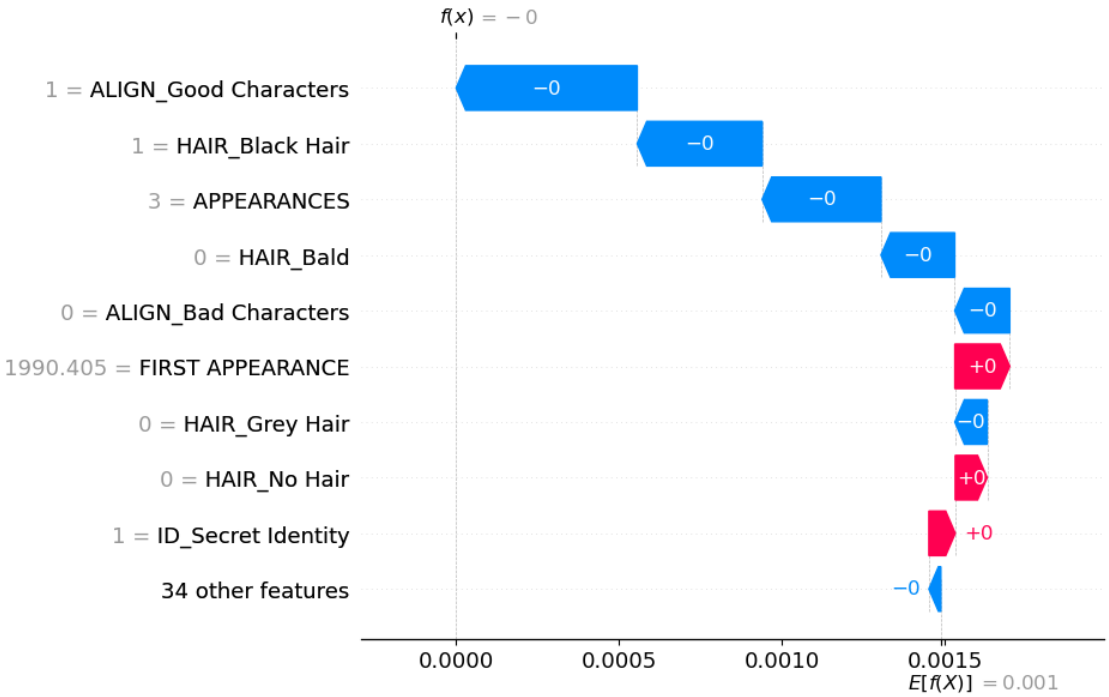

```
Created Summary plot for Marvel SEX predictions
Creating Waterfall plot for Marvel SEX predictions
```



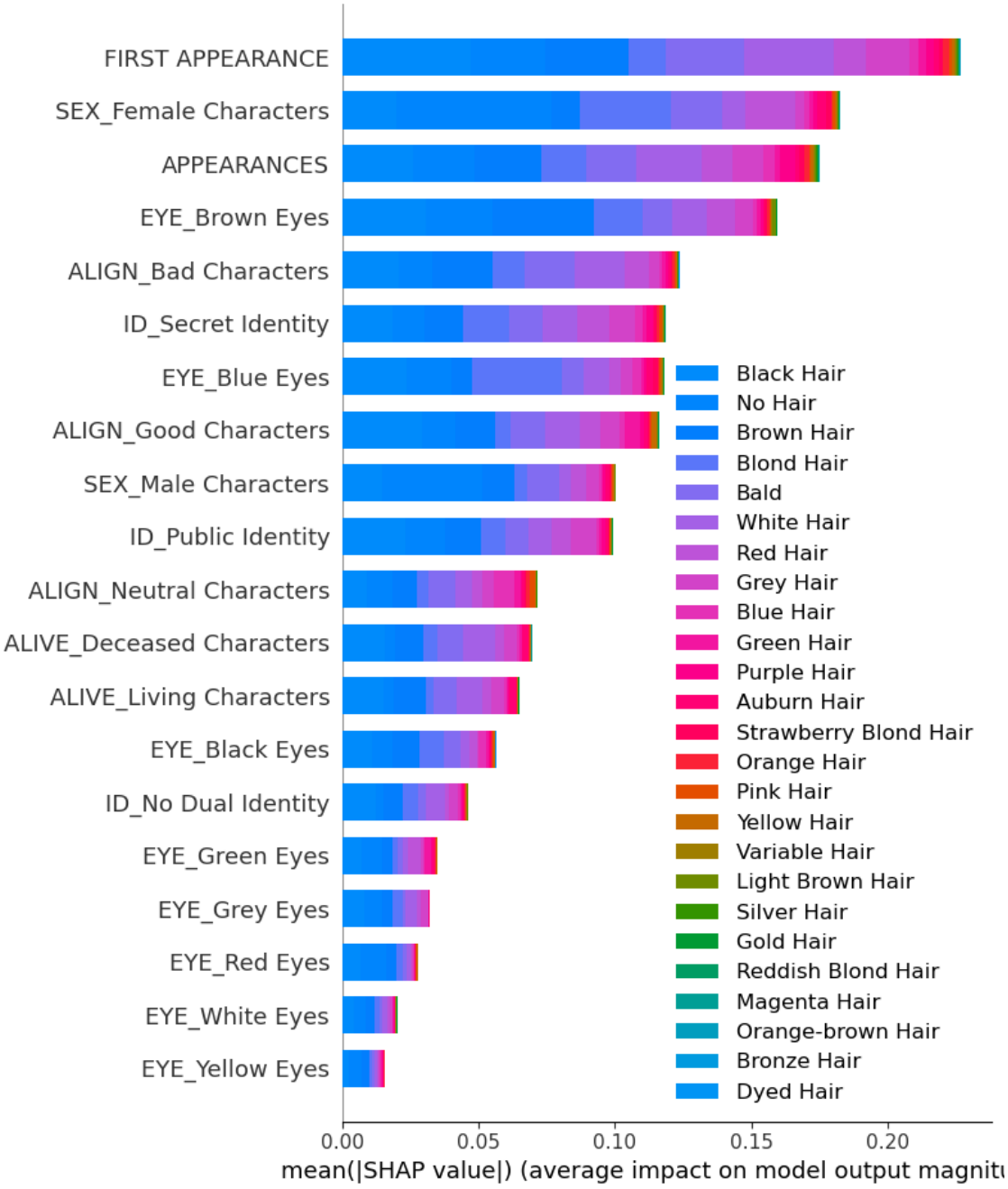

```
Created Waterfall plot for Marvel SEX predictions
Creating Summary plot for Marvel EYE predictions
```



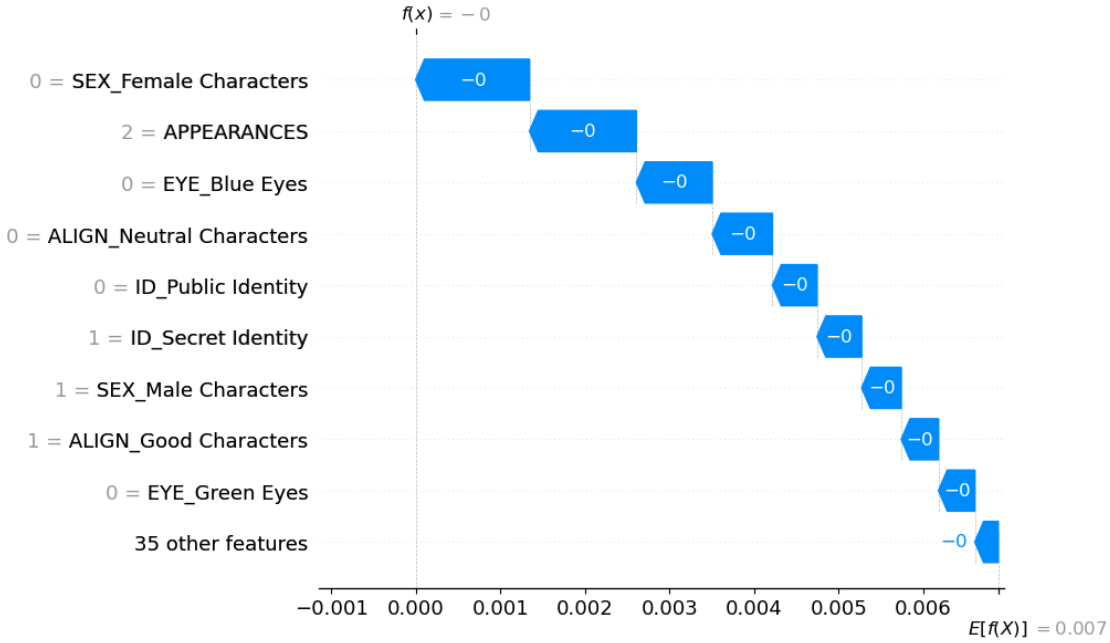

```
Created Summary plot for Marvel EYE predictions
Creating Waterfall plot for Marvel EYE predictions
```



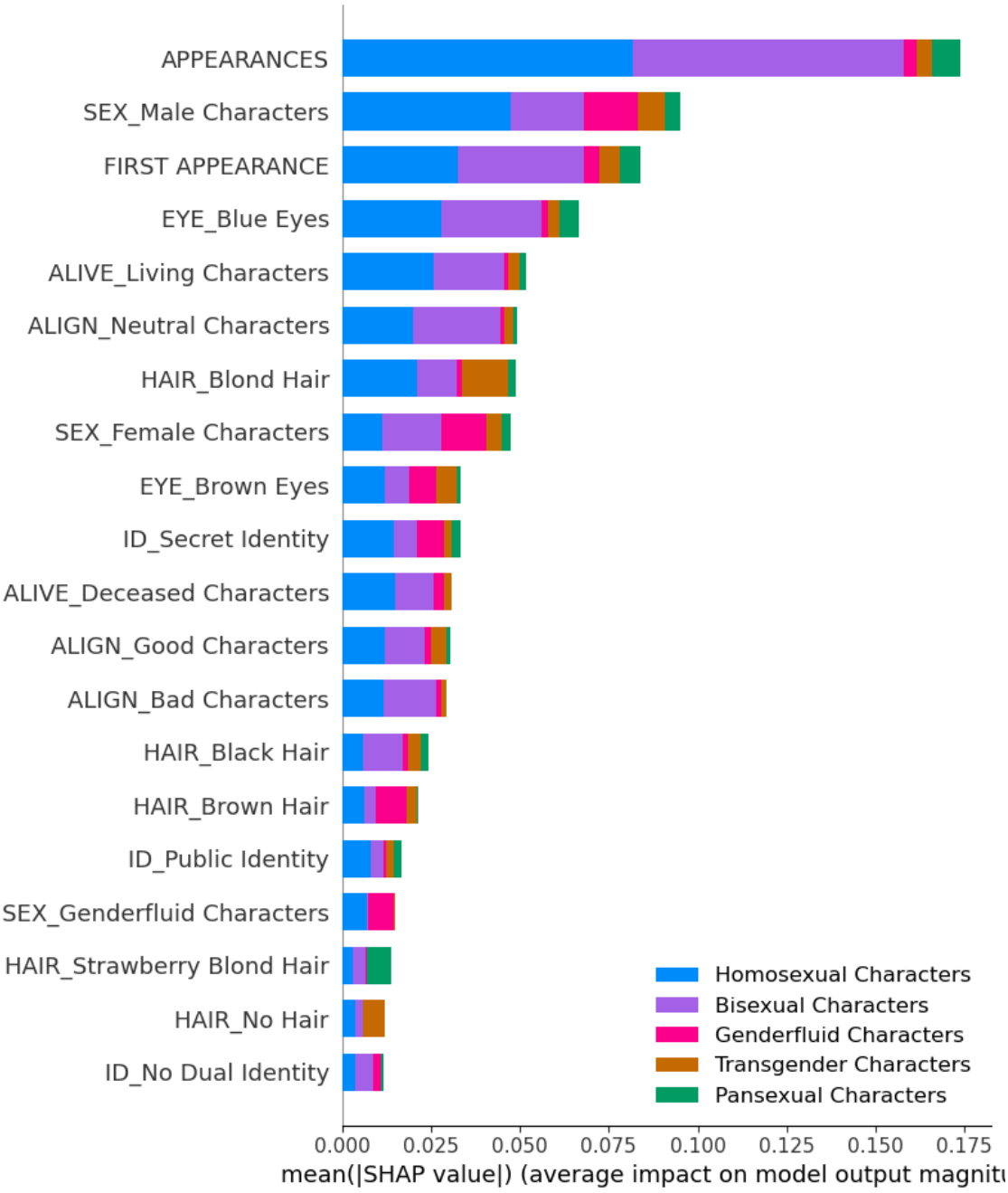

```
Created Waterfall plot for Marvel EYE predictions
Creating Summary plot for Marvel HAIR predictions
```



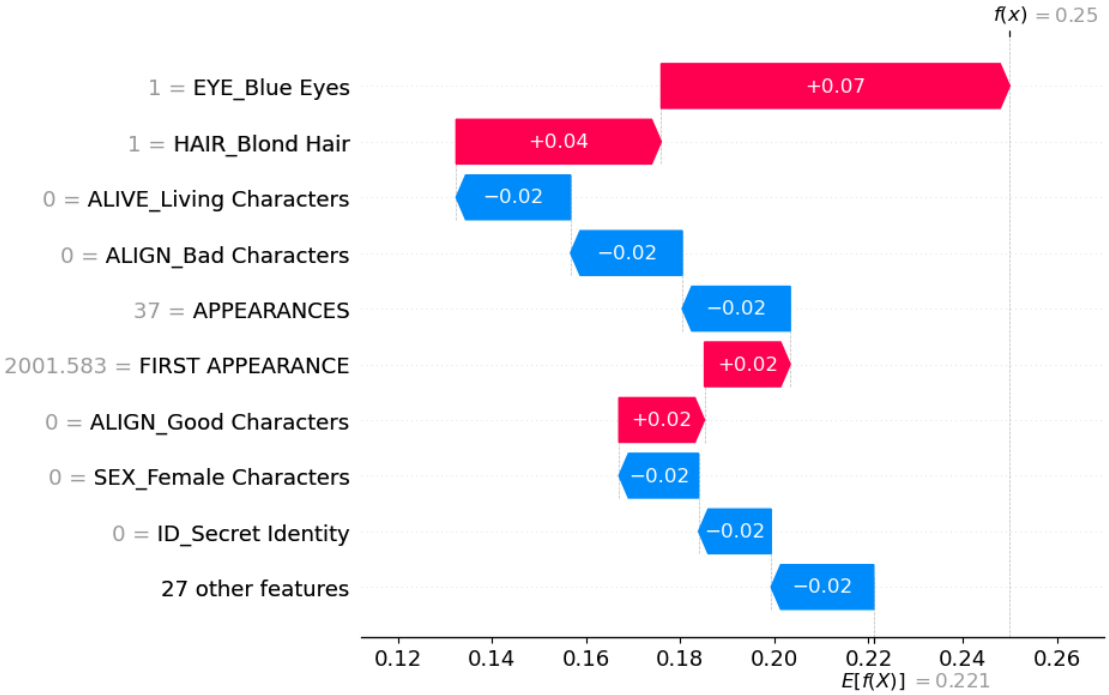

```
Created Summary plot for Marvel HAIR predictions
Creating Waterfall plot for Marvel HAIR predictions
```



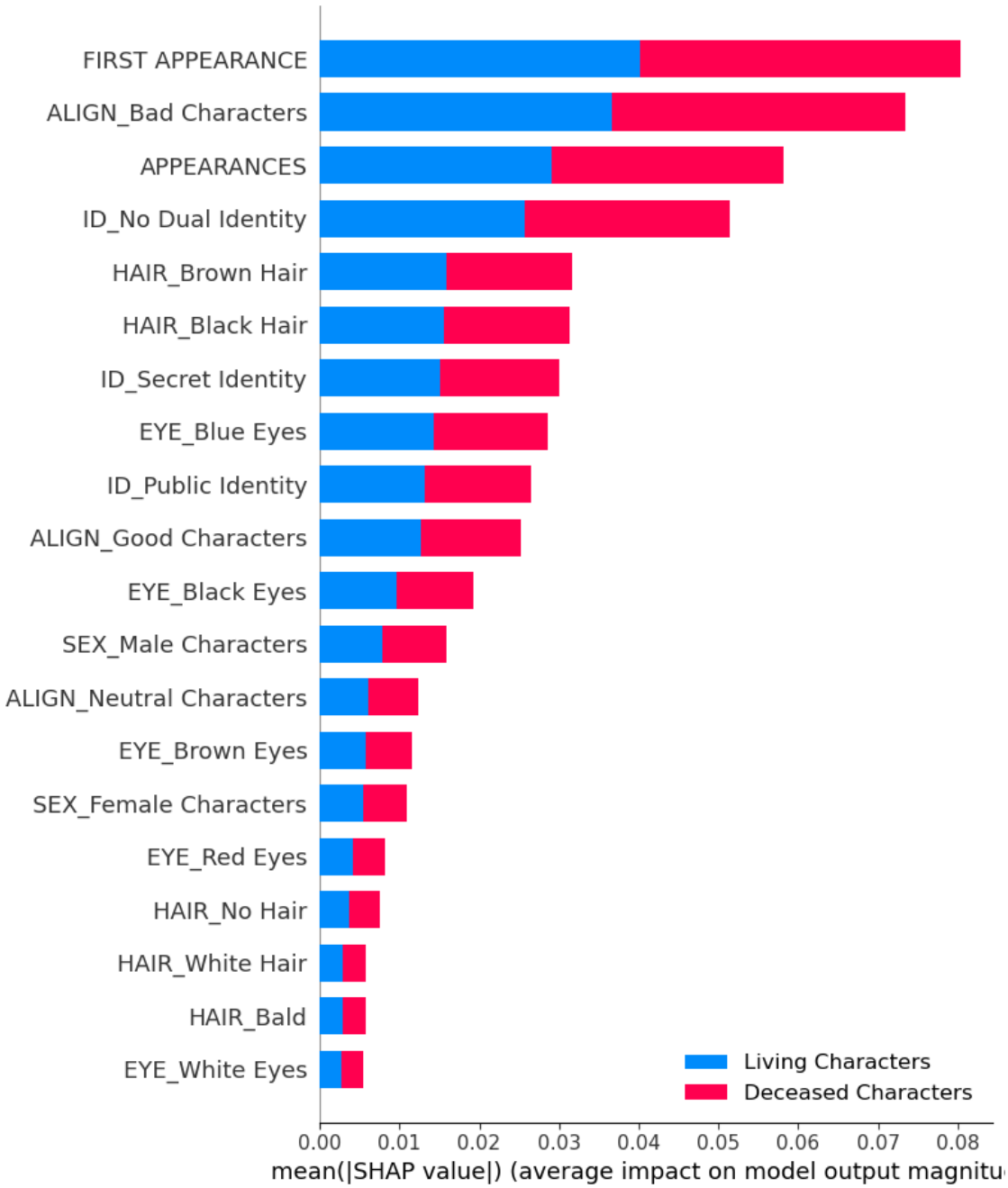

```
Created Waterfall plot for Marvel HAIR predictions
Creating Summary plot for Marvel GSM predictions
```



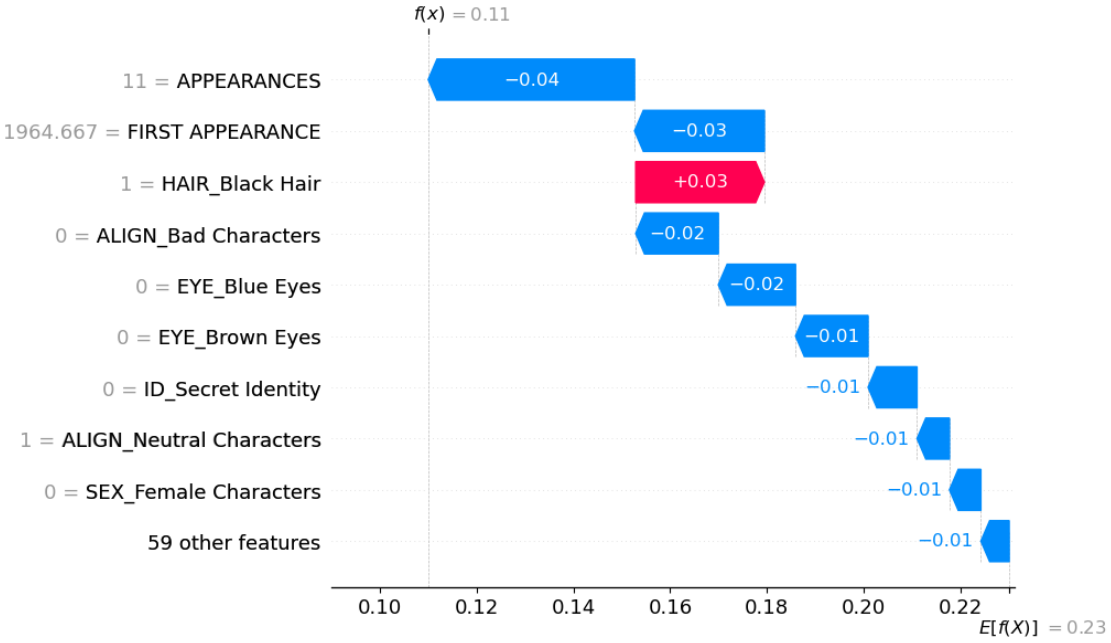

```
Created Summary plot for Marvel GSM predictions
Creating Waterfall plot for Marvel GSM predictions
```



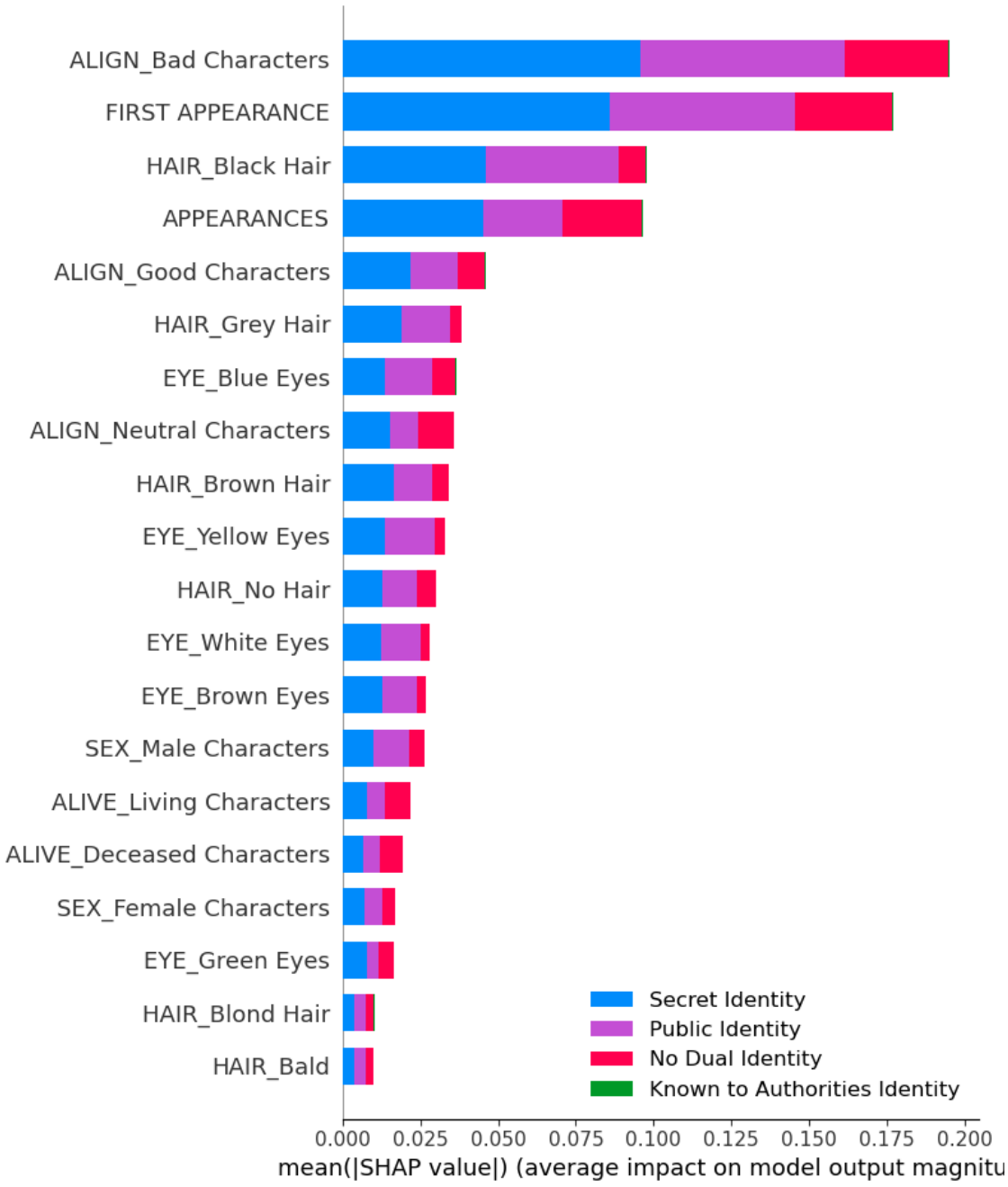

```
Created Waterfall plot for Marvel GSM predictions
Creating Summary plot for Marvel ALIVE predictions
```



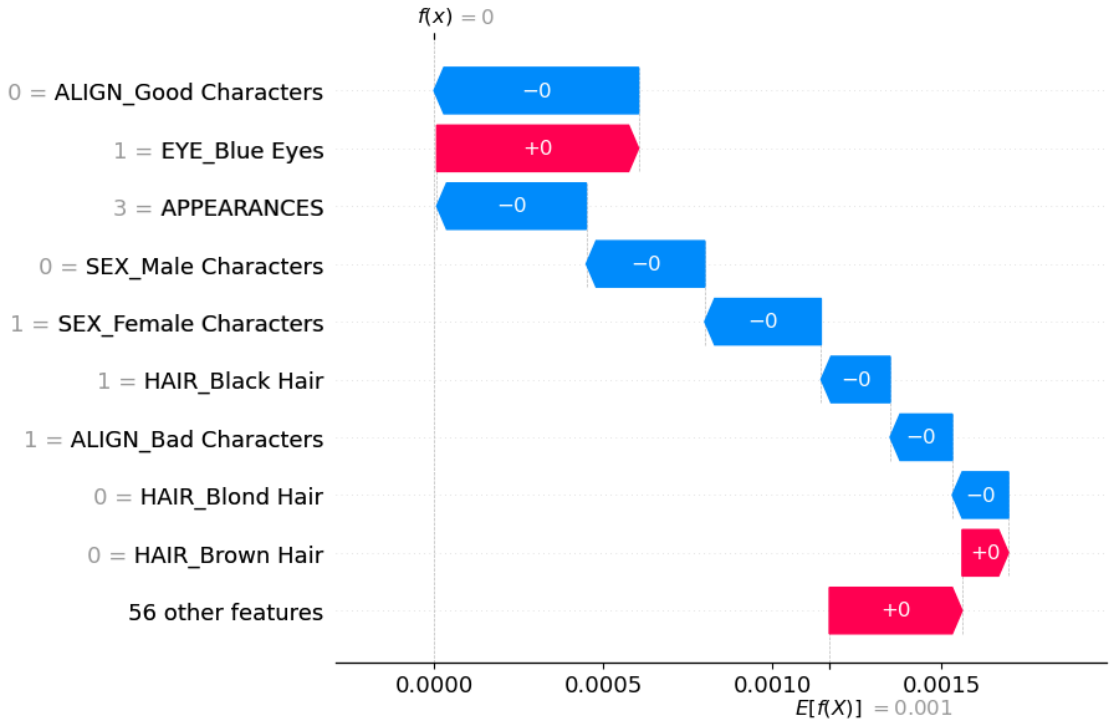

```
Created Summary plot for Marvel ALIVE predictions
Creating Waterfall plot for Marvel ALIVE predictions
```




```
Created Waterfall plot for Marvel ALIVE predictions
Creating Summary plot for Marvel ID predictions
```




```
Created Summary plot for Marvel ID predictions
Creating Waterfall plot for Marvel ID predictions
```

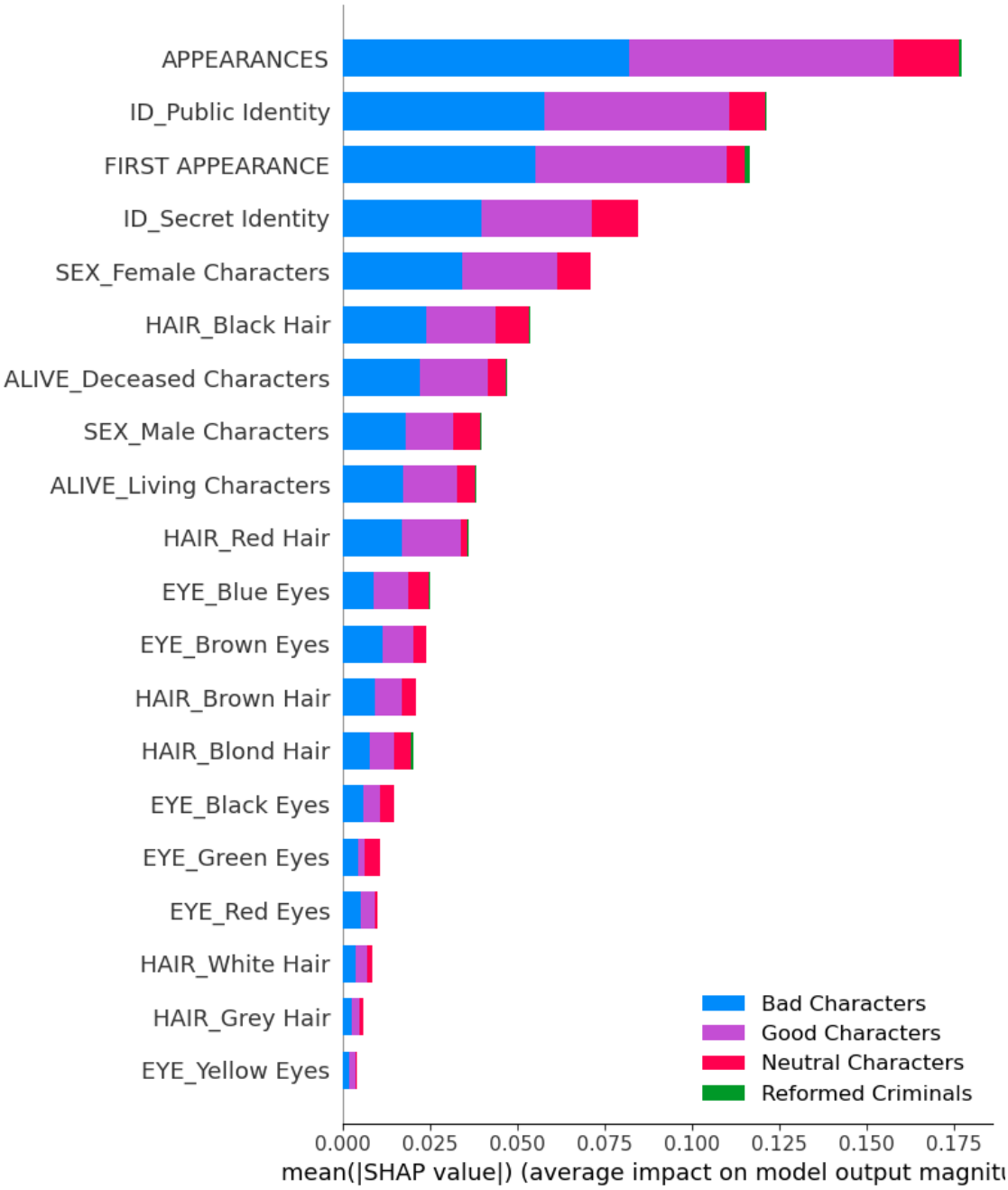



```
Created Waterfall plot for Marvel ID predictions
Marvel plots created
```

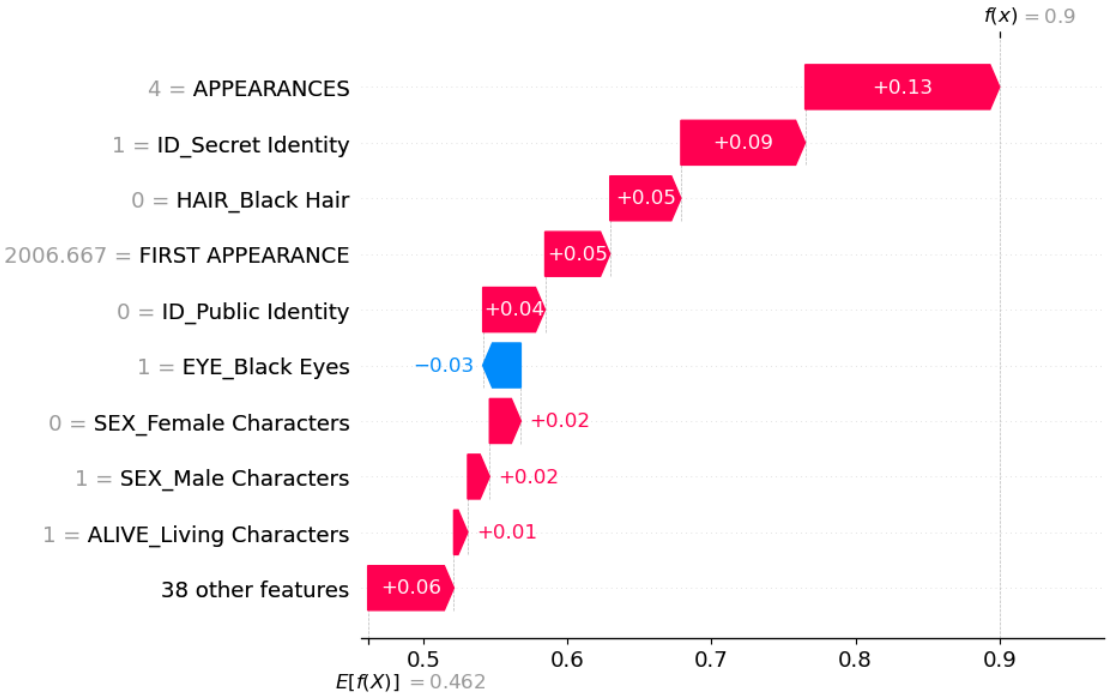
[ ]:
```
# Create plots for DC

for explainer, shap_values, feature_subset, target_feature, class_names in␣
 ↪shap_models_dc:
    sample_index = random.randint(0, len(feature_subset) - 1)

    print(f"""Creating Summary plot for DC {target_feature} predictions""")
    shap.summary_plot(shap_values, feature_subset, feature_names=feature_subset.
 ↪columns, show=False, class_names=class_names)
    plt.savefig(f"""figs/summary/DC_{target_feature}_summary.png""")
    plt.show()
    print(f"""Created Summary plot for DC {target_feature} predictions""")

    print(f"Creating Waterfall plot for DC {target_feature} predictions")
    shap.plots.waterfall(shap.Explanation(values=shap_values[0][sample_index],␣
 ↪base_values=explainer.expected_value[0], data=feature_subset.
 ↪iloc[sample_index]), max_display=10, show=False)
    plt.savefig(f"figs/waterfall/DC_{target_feature}_{sample_index}_waterfall.
 ↪png")
    plt.show()
```

```
    print(f"Created Waterfall plot for DC {target_feature} predictions")


print("DC plots created")
```

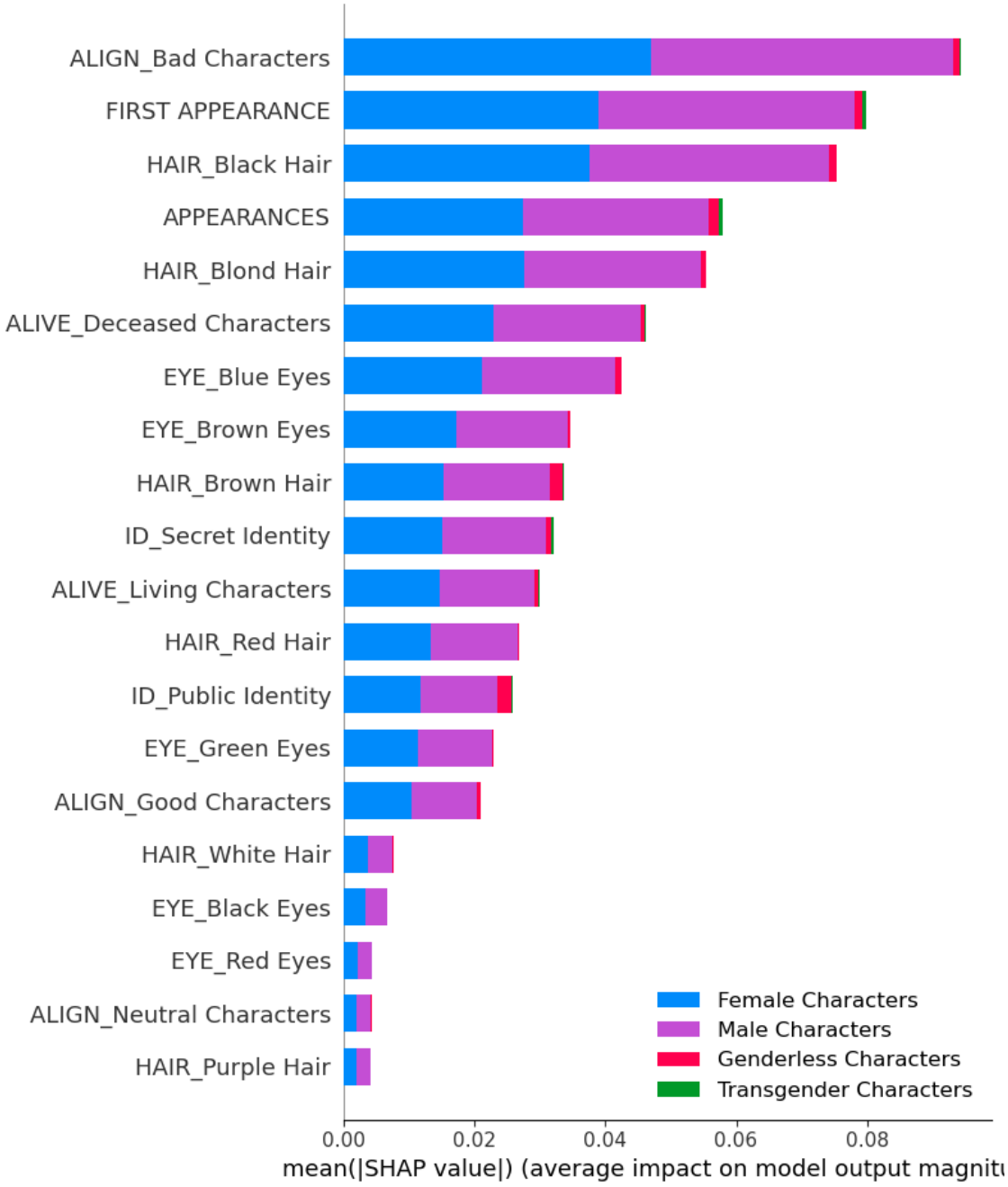
```
Creating Summary plot for DC ALIGN predictions
```



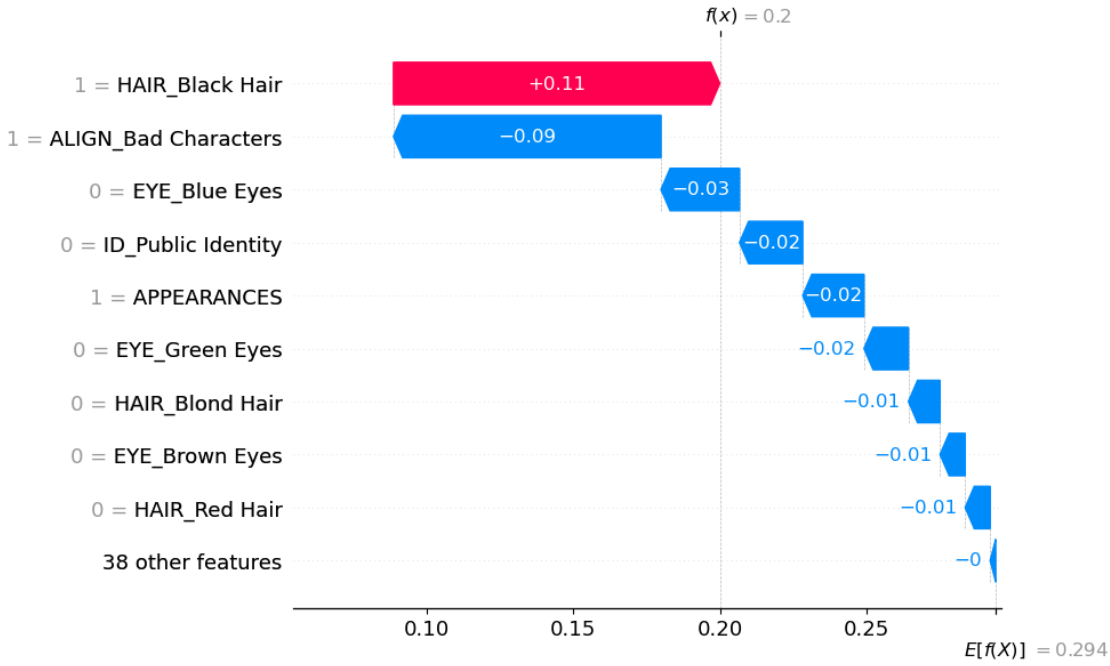
```
Created Summary plot for DC ALIGN predictions
Creating Waterfall plot for DC ALIGN predictions
```



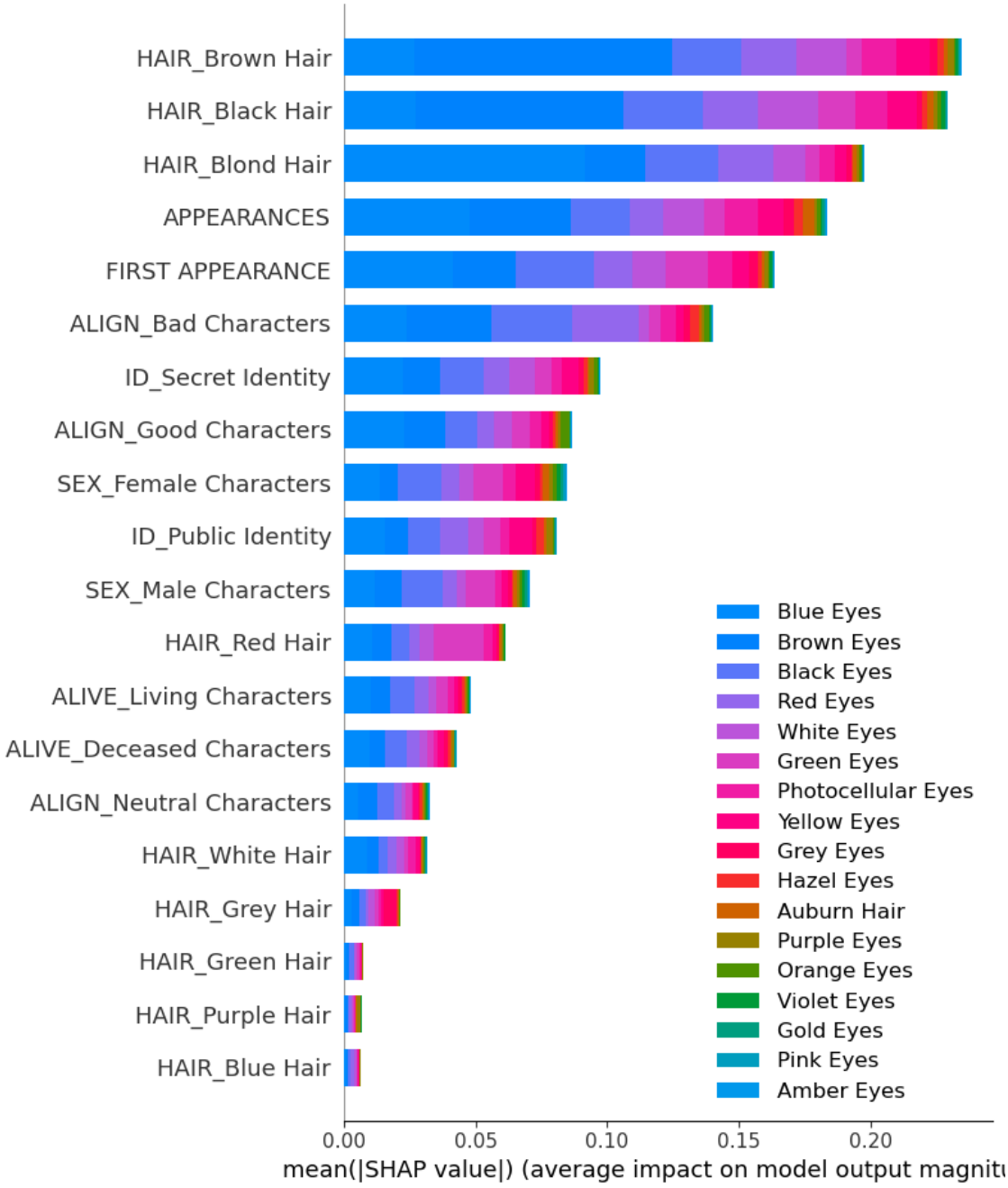

```
Created Waterfall plot for DC ALIGN predictions
Creating Summary plot for DC SEX predictions
```



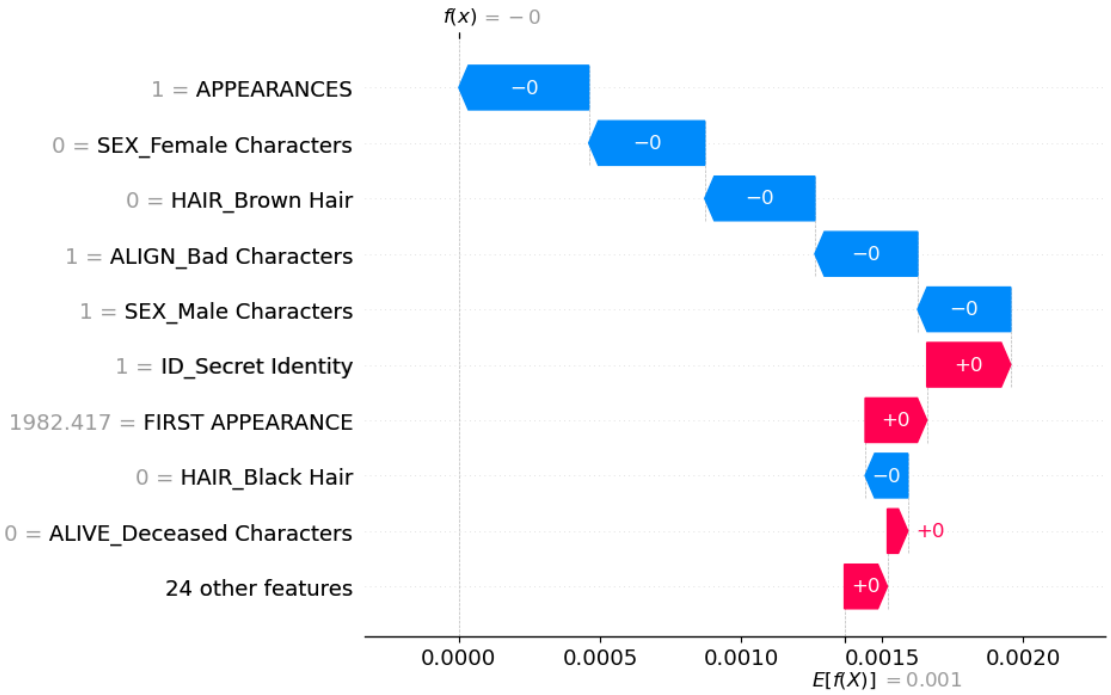

```
Created Summary plot for DC SEX predictions
Creating Waterfall plot for DC SEX predictions
```



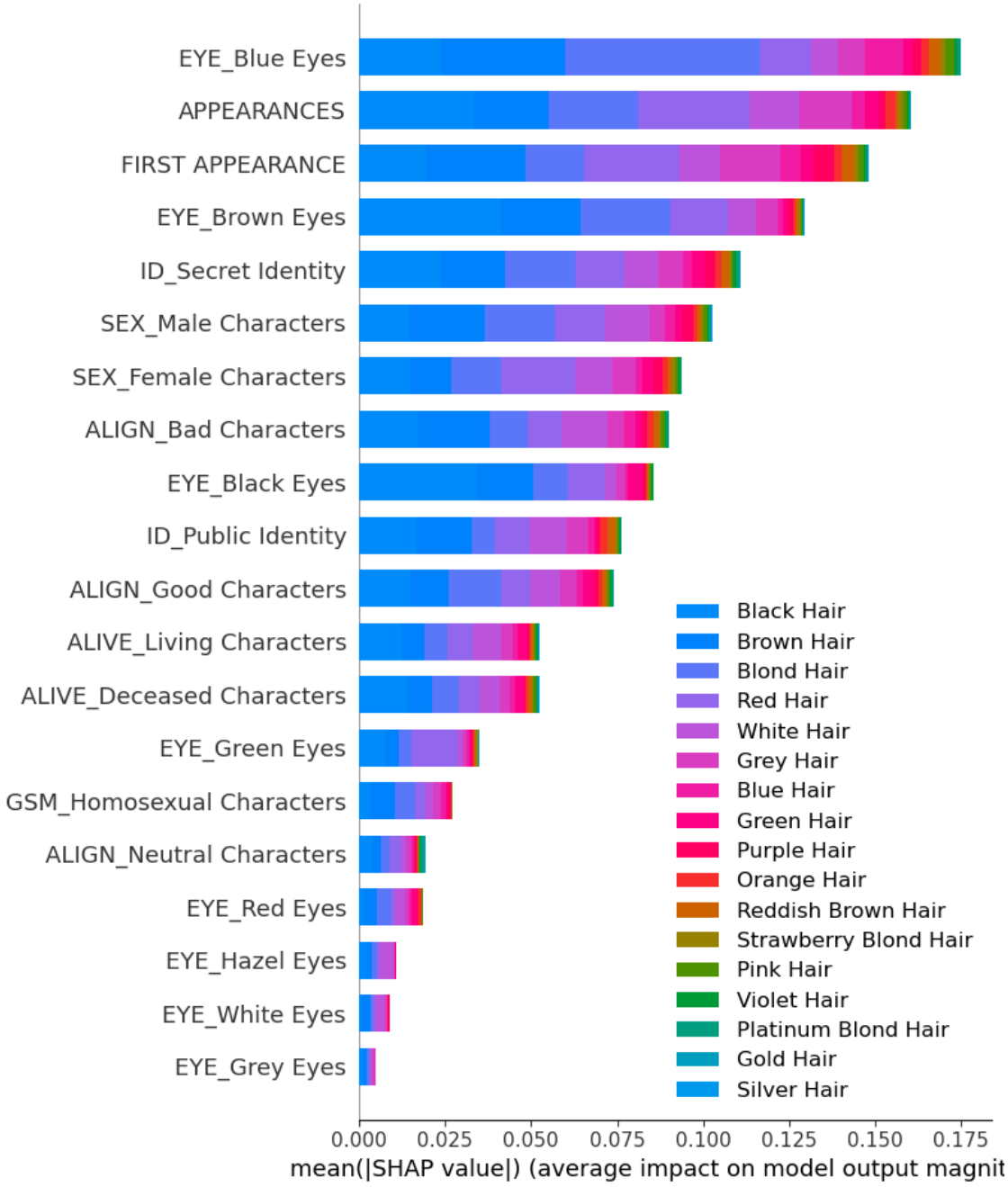

```
Created Waterfall plot for DC SEX predictions
Creating Summary plot for DC EYE predictions
```



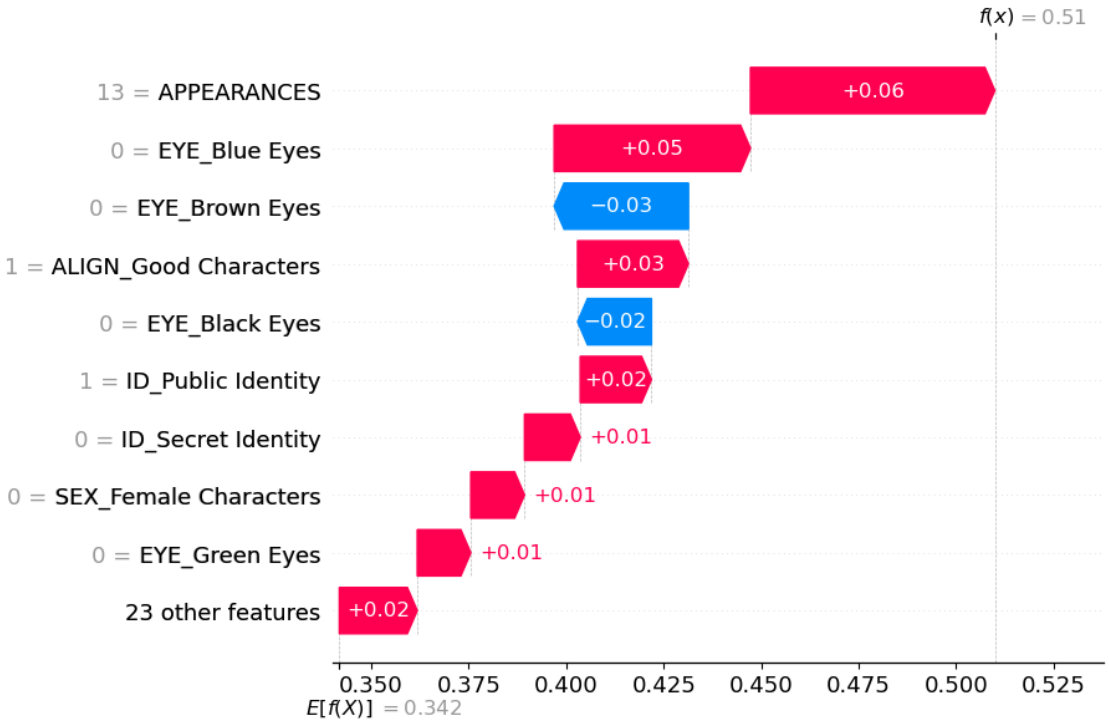

```
Created Summary plot for DC EYE predictions
Creating Waterfall plot for DC EYE predictions
```



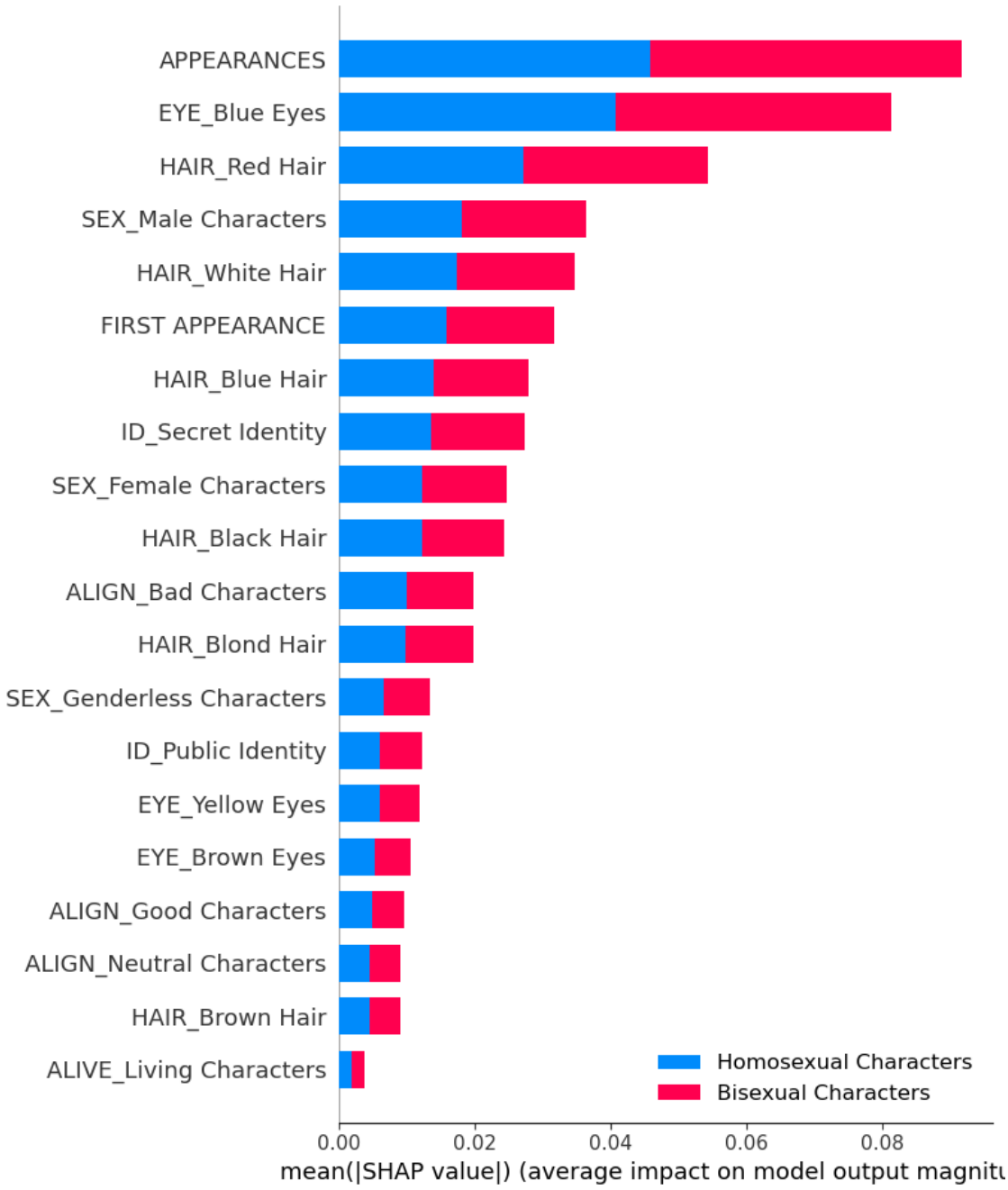

```
Created Waterfall plot for DC EYE predictions
Creating Summary plot for DC HAIR predictions
```



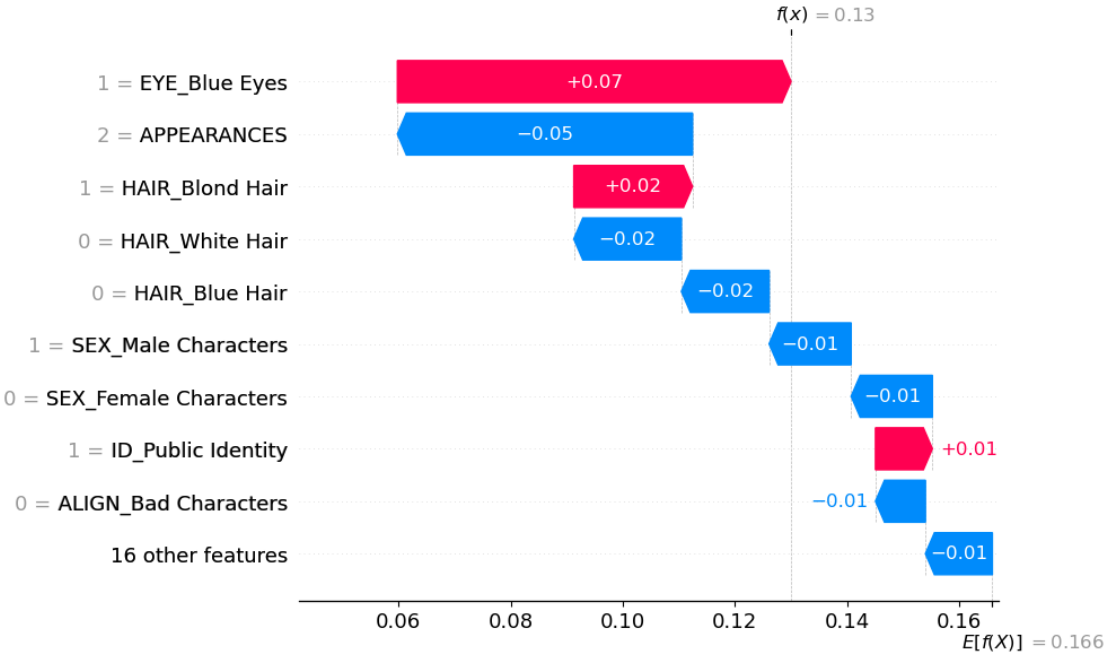

```
Created Summary plot for DC HAIR predictions
Creating Waterfall plot for DC HAIR predictions
```



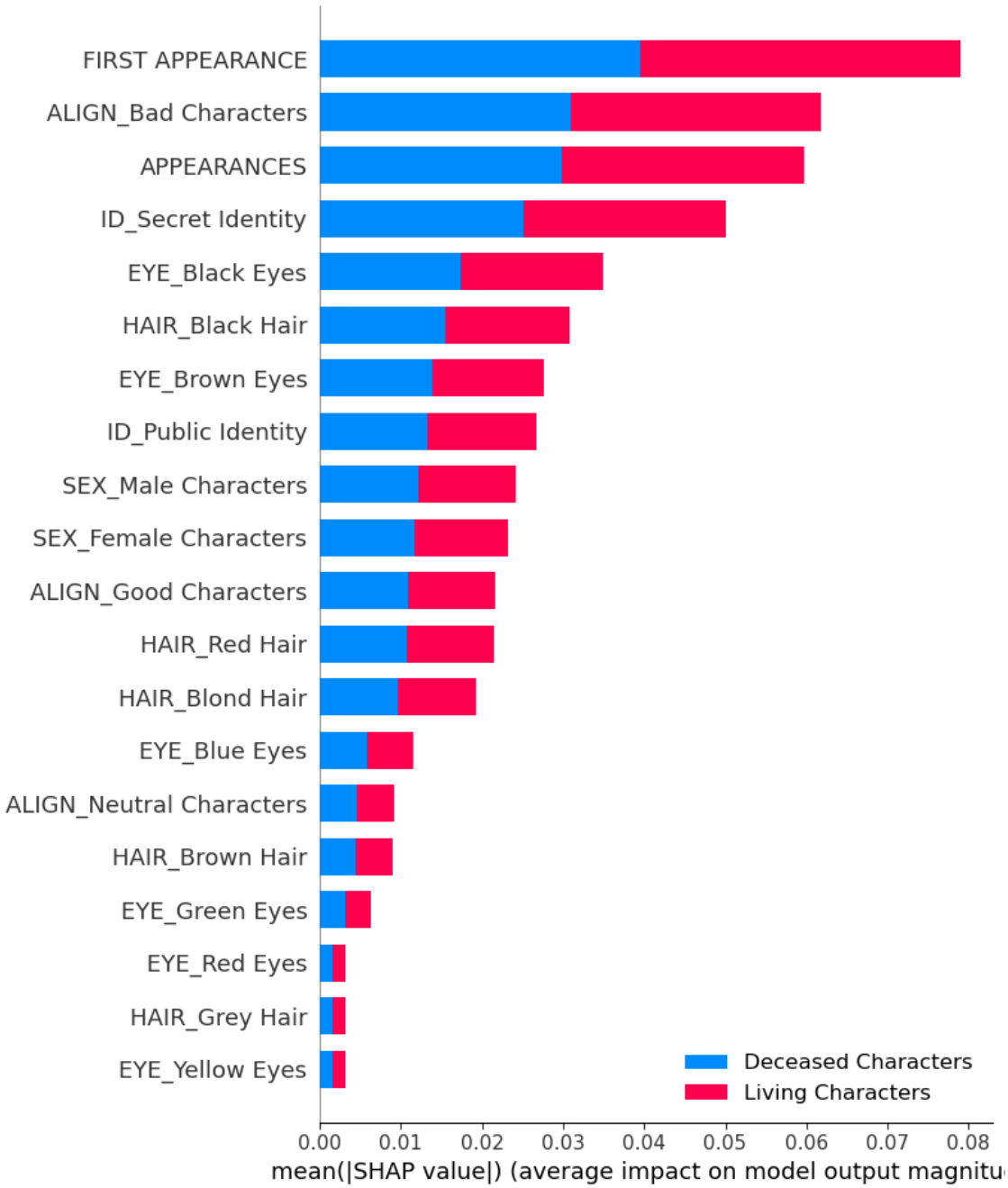

```
Created Waterfall plot for DC HAIR predictions
Creating Summary plot for DC GSM predictions
```



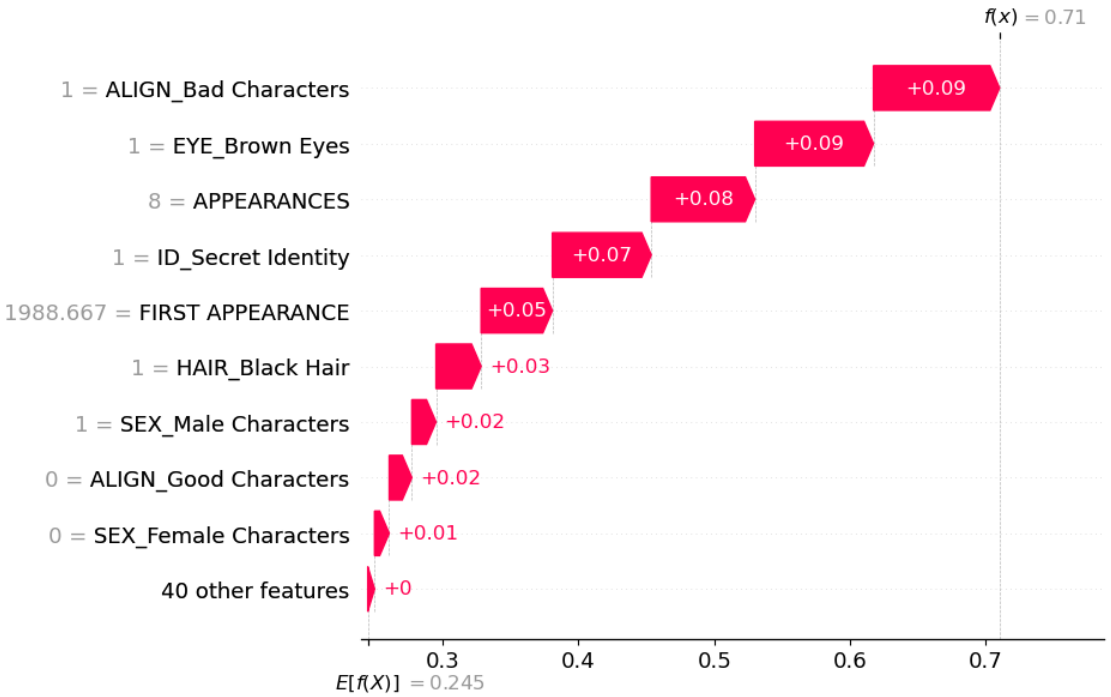

```
Created Summary plot for DC GSM predictions
Creating Waterfall plot for DC GSM predictions
```



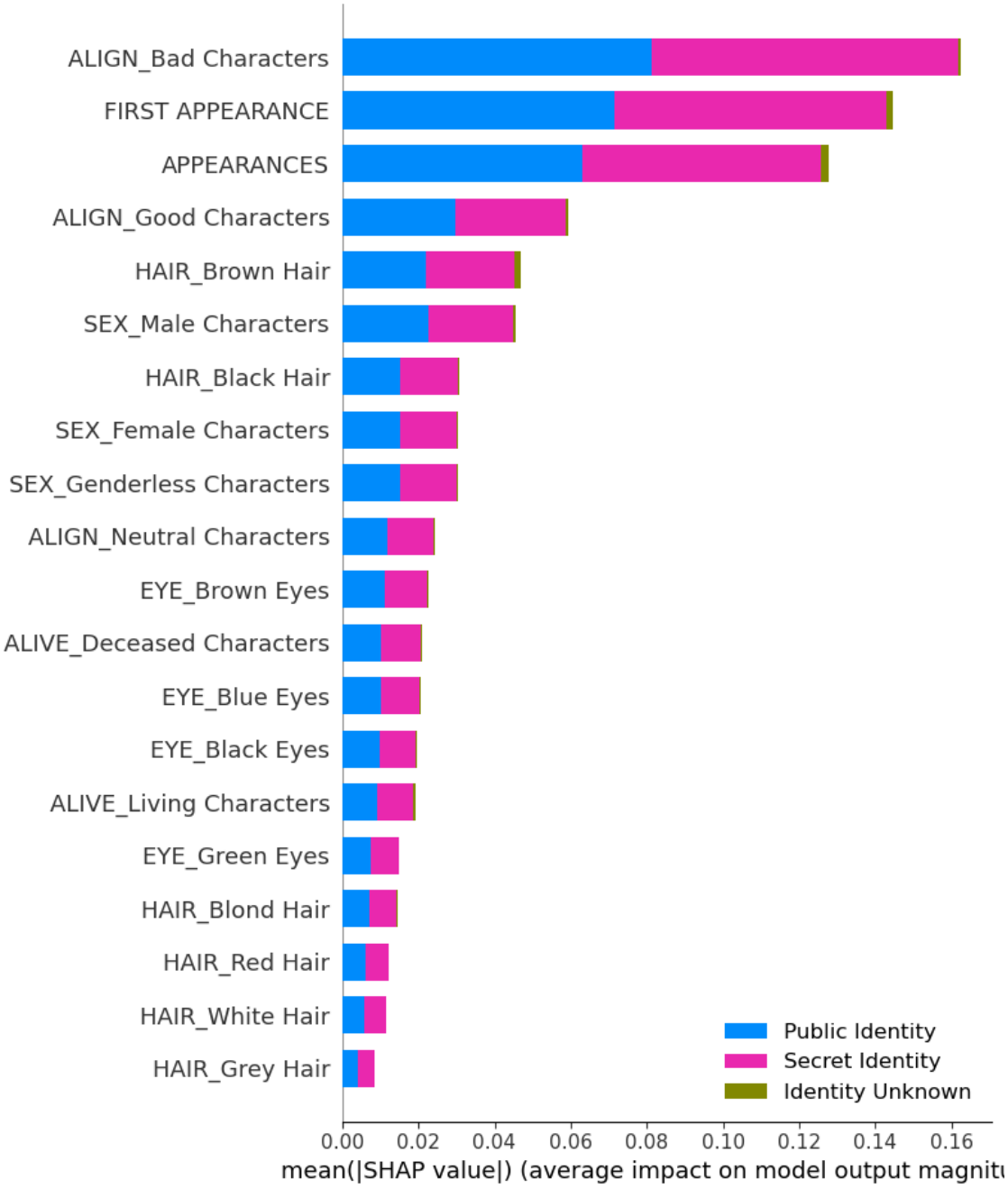

```
Created Waterfall plot for DC GSM predictions
Creating Summary plot for DC ALIVE predictions
```



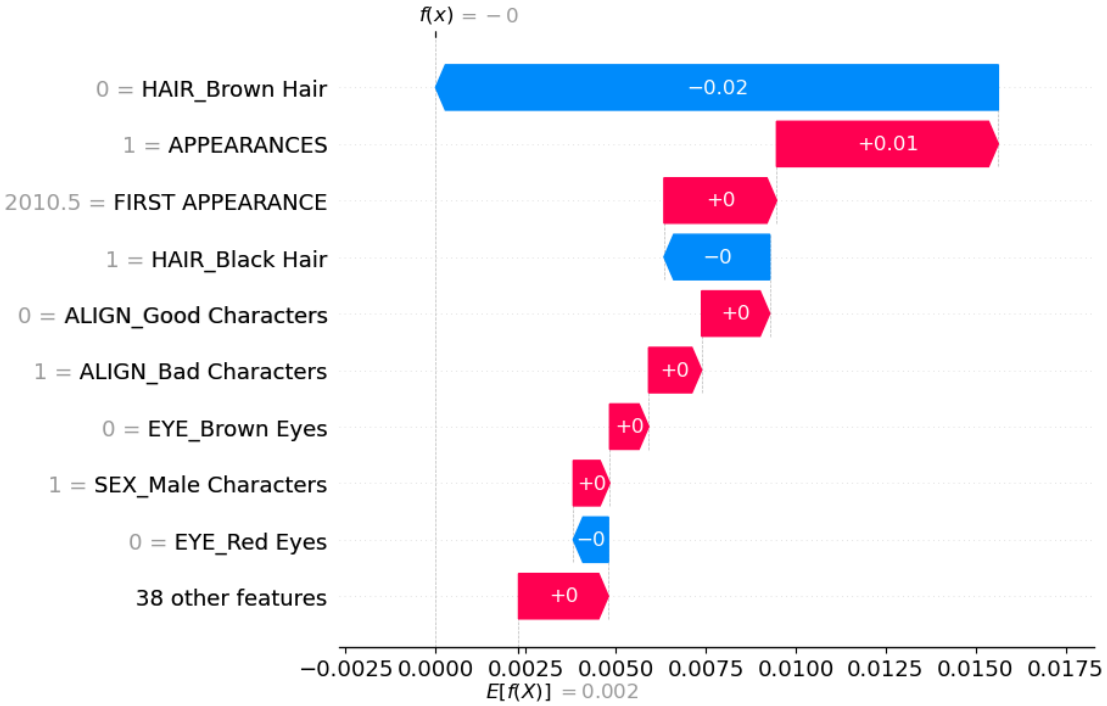

```
Created Summary plot for DC ALIVE predictions
Creating Waterfall plot for DC ALIVE predictions
```




```
Created Waterfall plot for DC ALIVE predictions
Creating Summary plot for DC ID predictions
```




```
Created Summary plot for DC ID predictions
Creating Waterfall plot for DC ID predictions
```

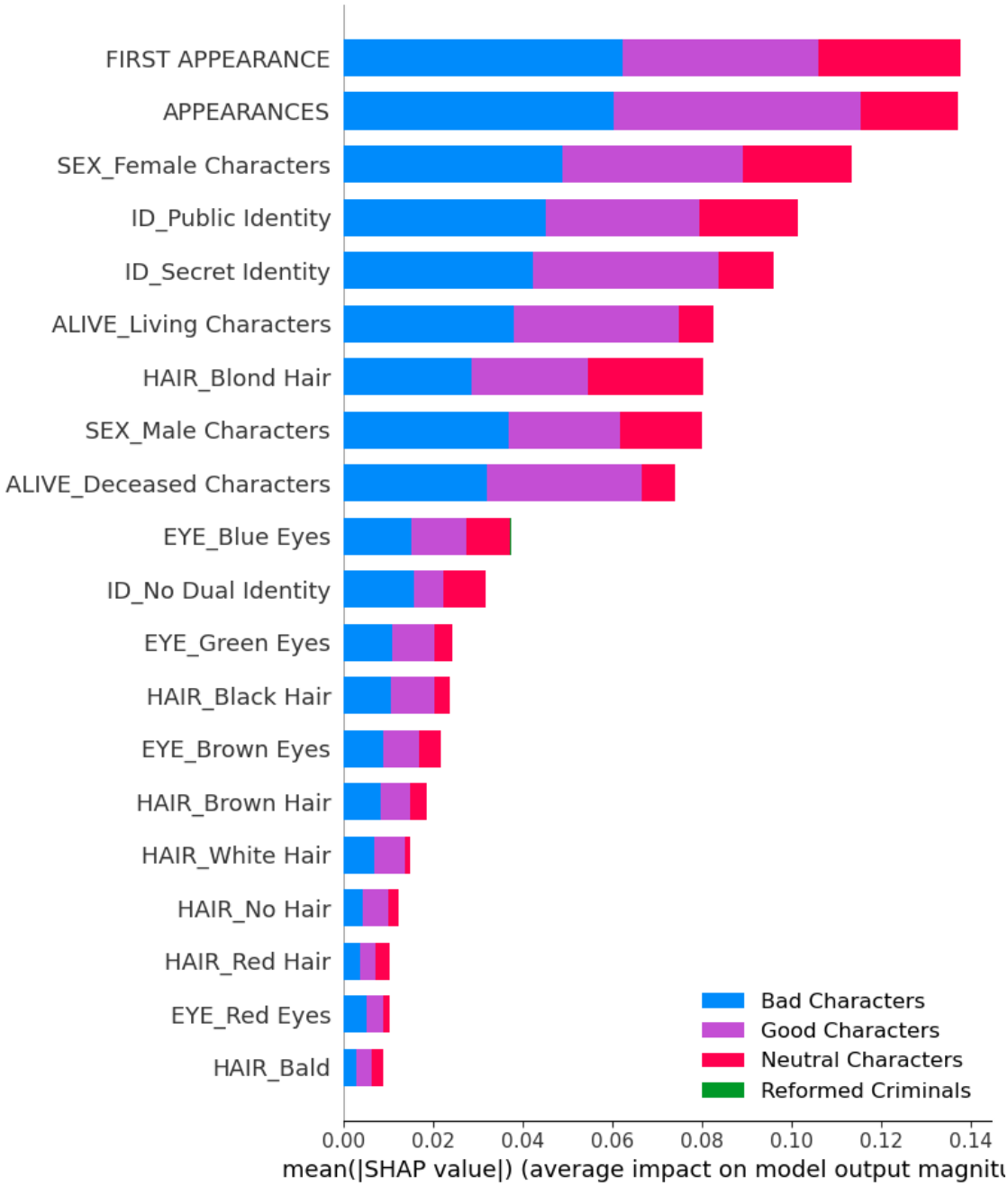



```
Created Waterfall plot for DC ID predictions
DC plots created
```

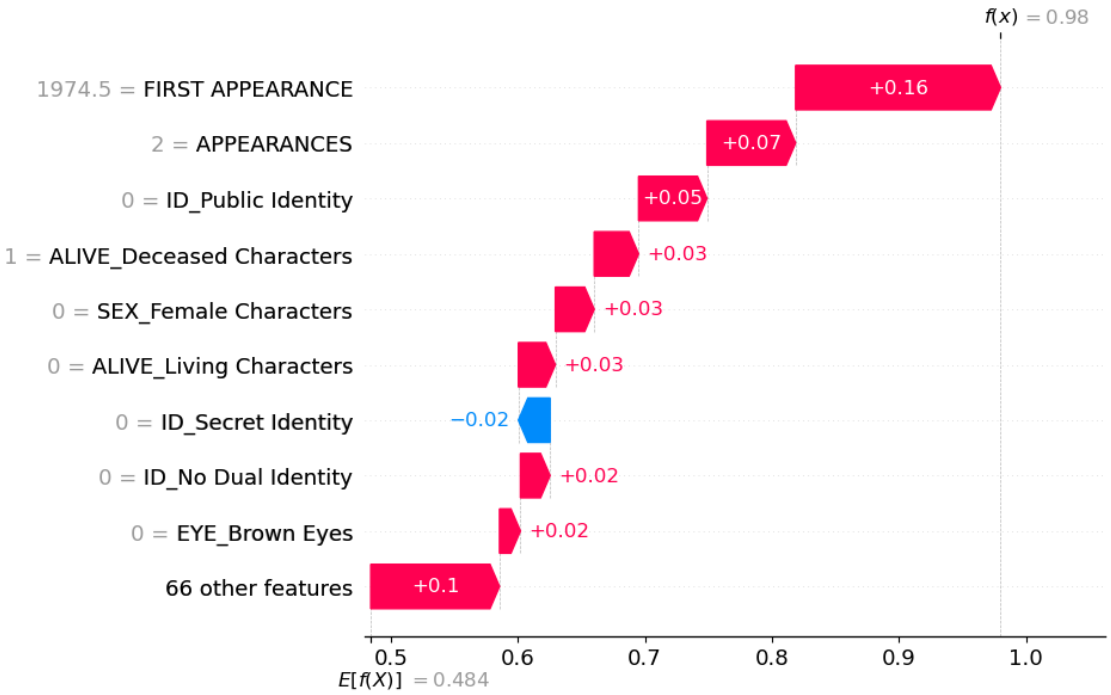
[ ]:
```
# Create plots for Combined

for explainer, shap_values, feature_subset, target_feature, class_names in␣
 ↪shap_models_combined:
    sample_index = random.randint(0, len(feature_subset) - 1)

    print(f"""Creating Summary plot for Combined {target_feature}␣
 ↪predictions""")
    shap.summary_plot(shap_values, feature_subset, feature_names=feature_subset.
 ↪columns, show=False, class_names=class_names)
    plt.savefig(f"""figs/summary/Combined_{target_feature}_summary.png""")
    plt.show()
    print(f"""Created Summary plot for Combined {target_feature} predictions""")

    print(f"Creating Waterfall plot for Combined {target_feature} predictions")
    shap.plots.waterfall(shap.Explanation(values=shap_values[0][sample_index],␣
 ↪base_values=explainer.expected_value[0], data=feature_subset.
 ↪iloc[sample_index]), max_display=10, show=False)
    plt.savefig(f"figs/waterfall/
 ↪Combined_{target_feature}_{sample_index}_waterfall.png")
    plt.show()
```

```
    print(f"Created Waterfall plot for Combined {target_feature} predictions")

print("Combined plots created")
```

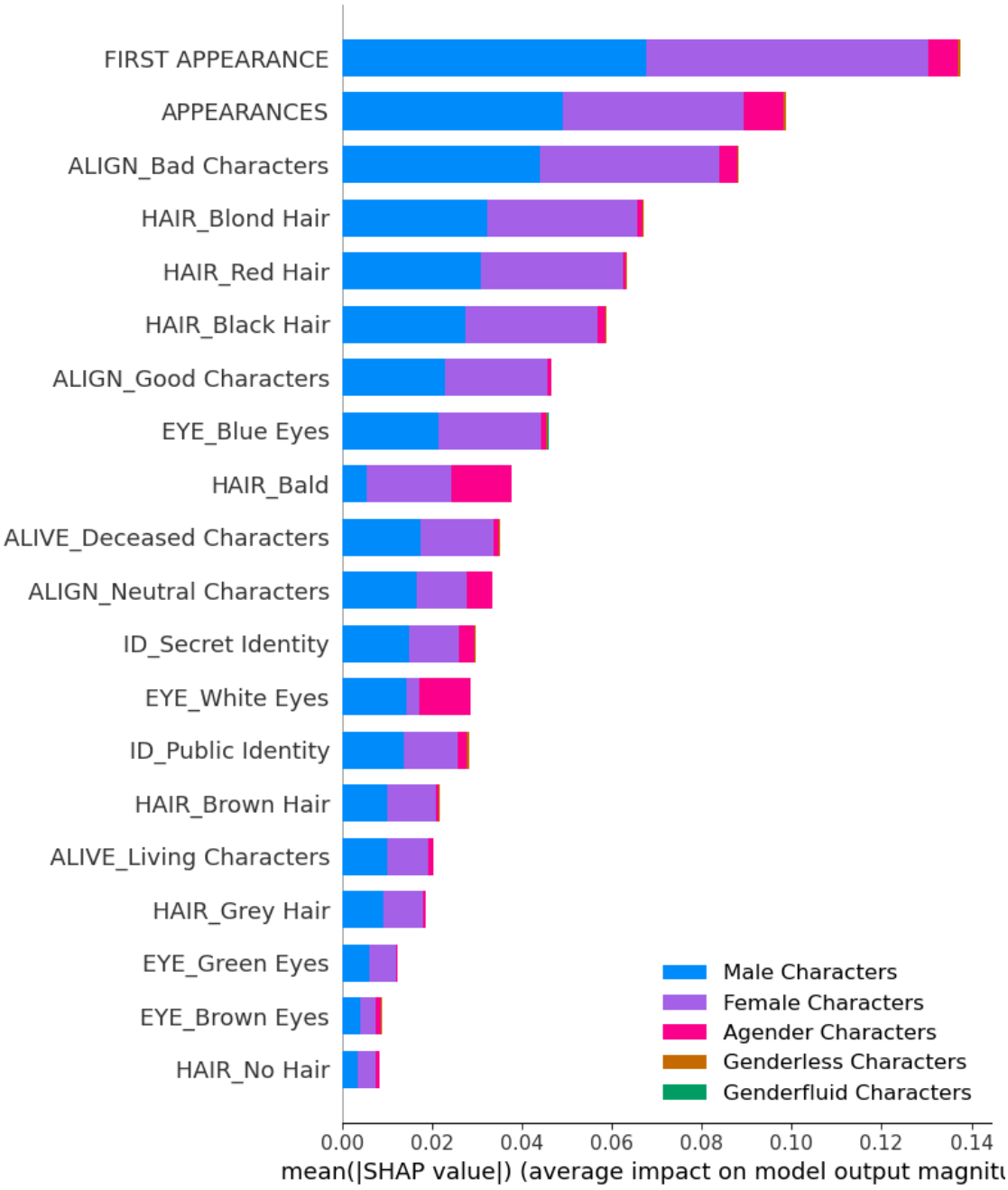
```
Creating Summary plot for Combined ALIGN predictions
```



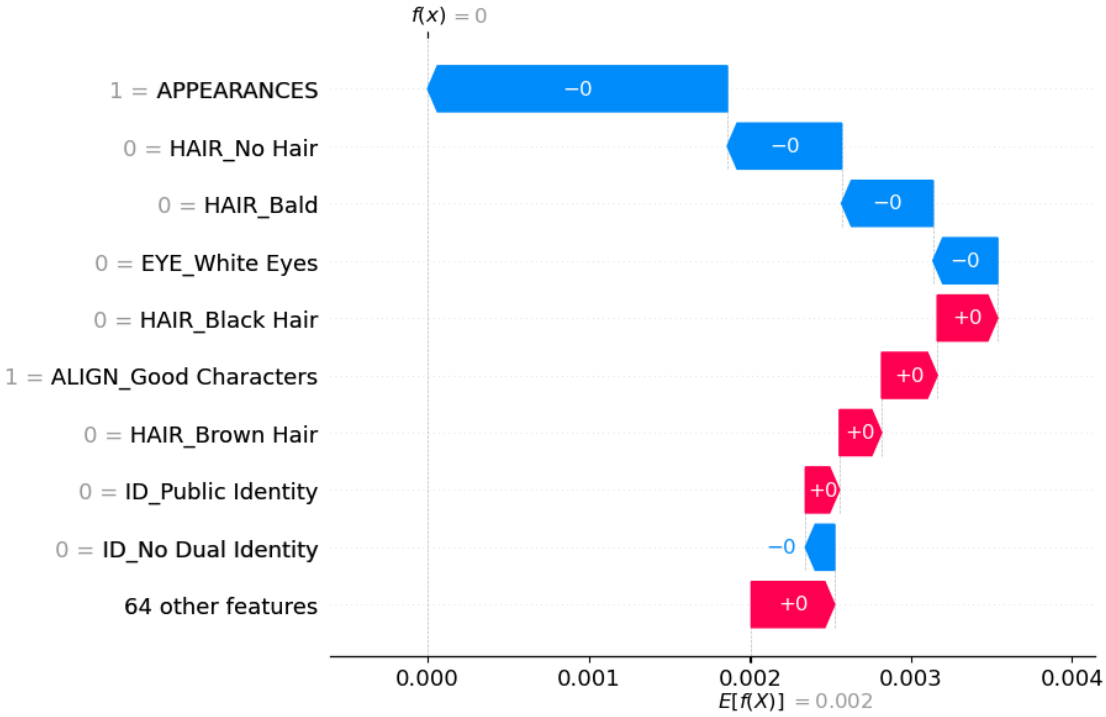

```
Created Summary plot for Combined ALIGN predictions
Creating Waterfall plot for Combined ALIGN predictions
```



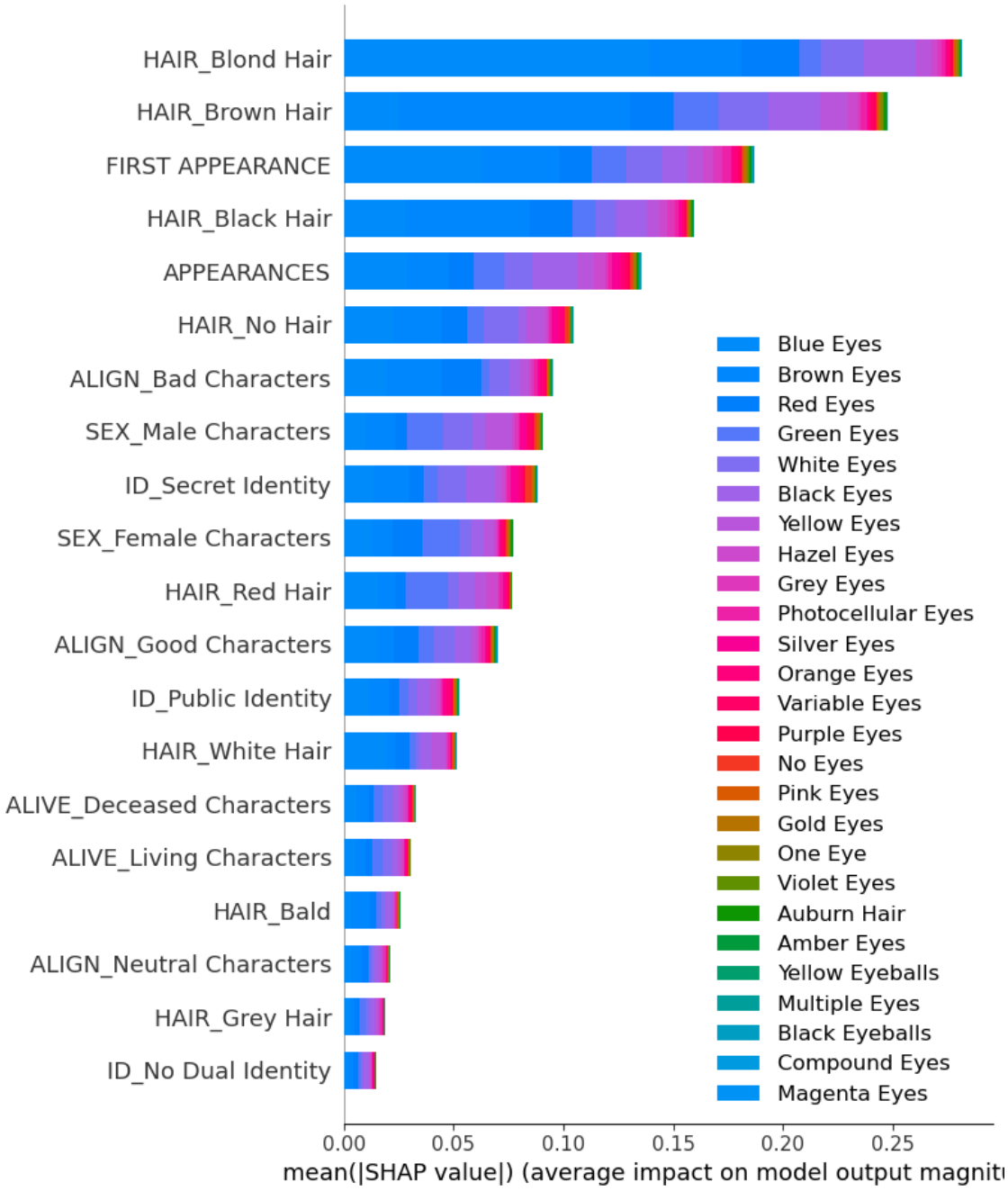

```
Created Waterfall plot for Combined ALIGN predictions
Creating Summary plot for Combined SEX predictions
```



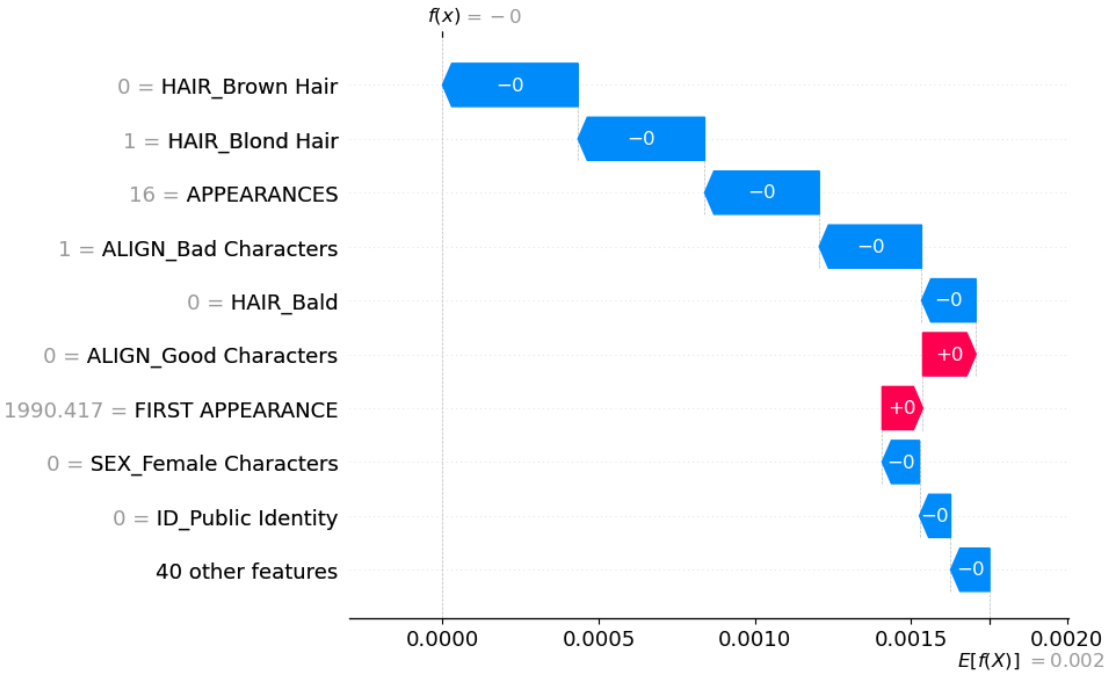

```
Created Summary plot for Combined SEX predictions
Creating Waterfall plot for Combined SEX predictions
```



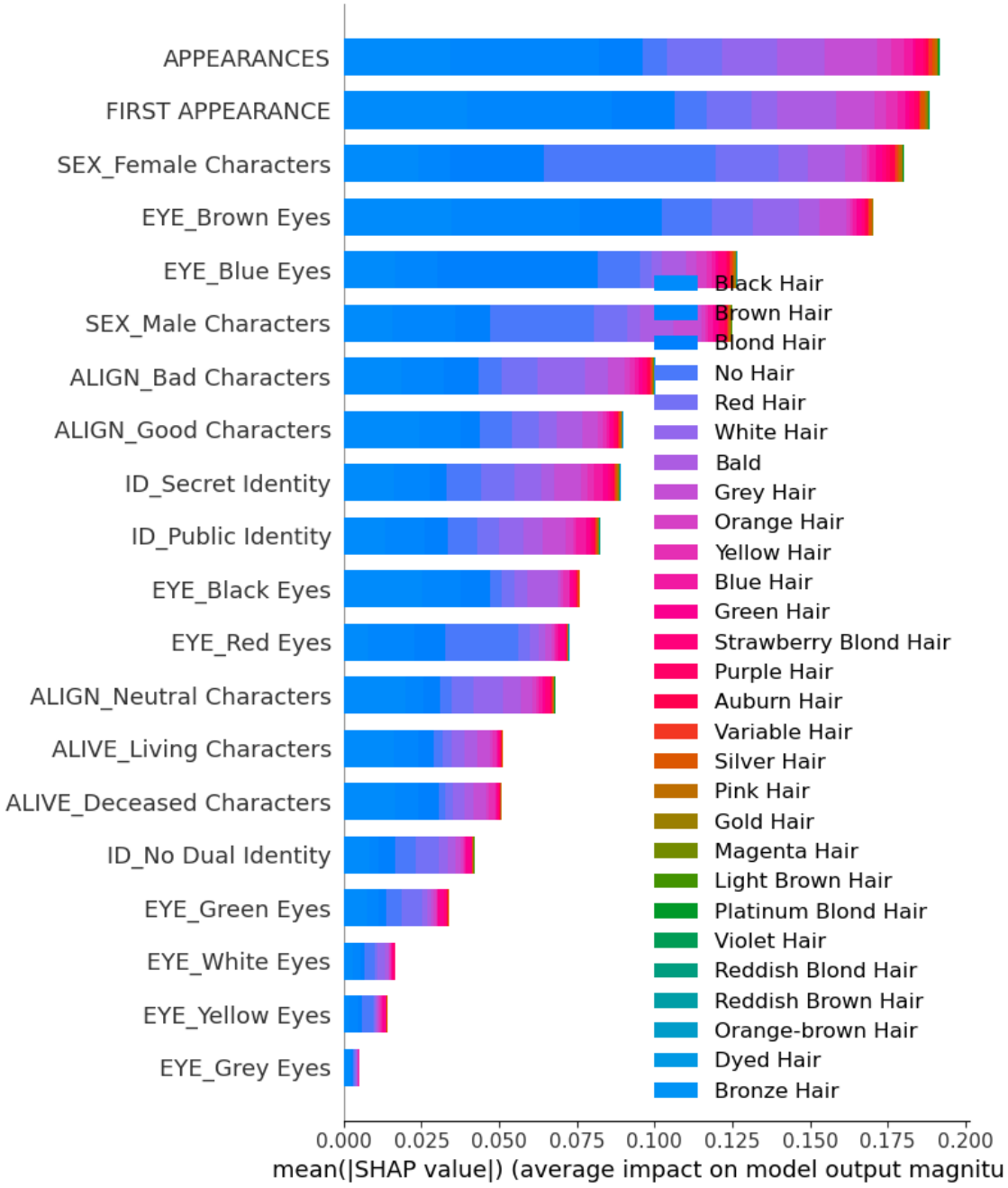

```
Created Waterfall plot for Combined SEX predictions
Creating Summary plot for Combined EYE predictions
```



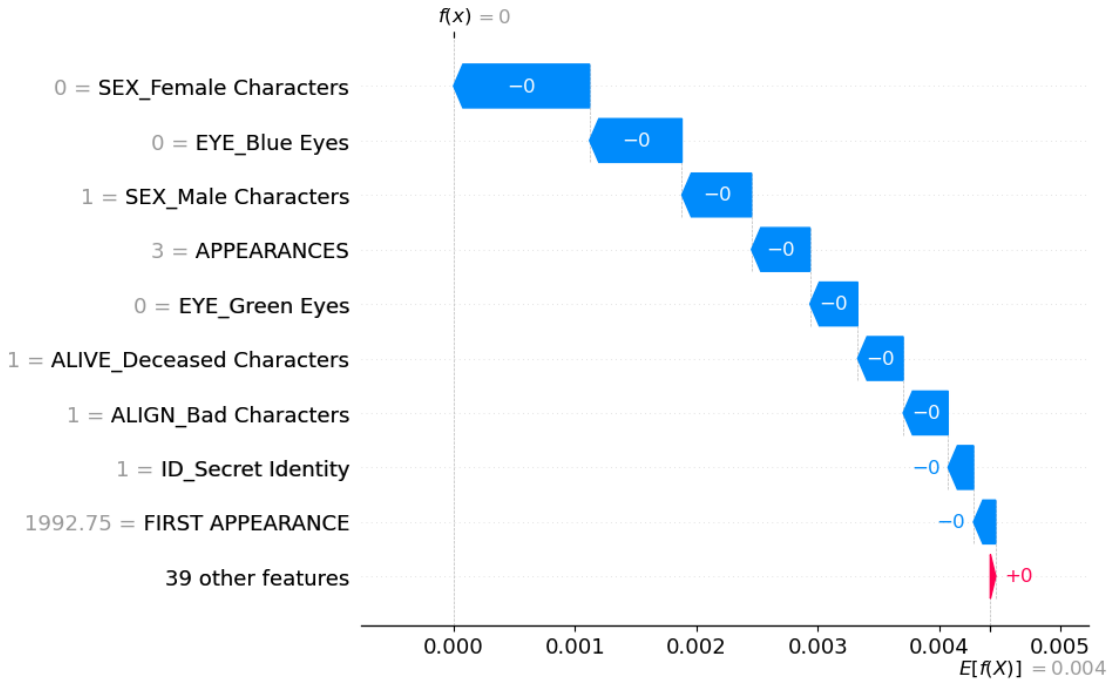

```
Created Summary plot for Combined EYE predictions
Creating Waterfall plot for Combined EYE predictions
```



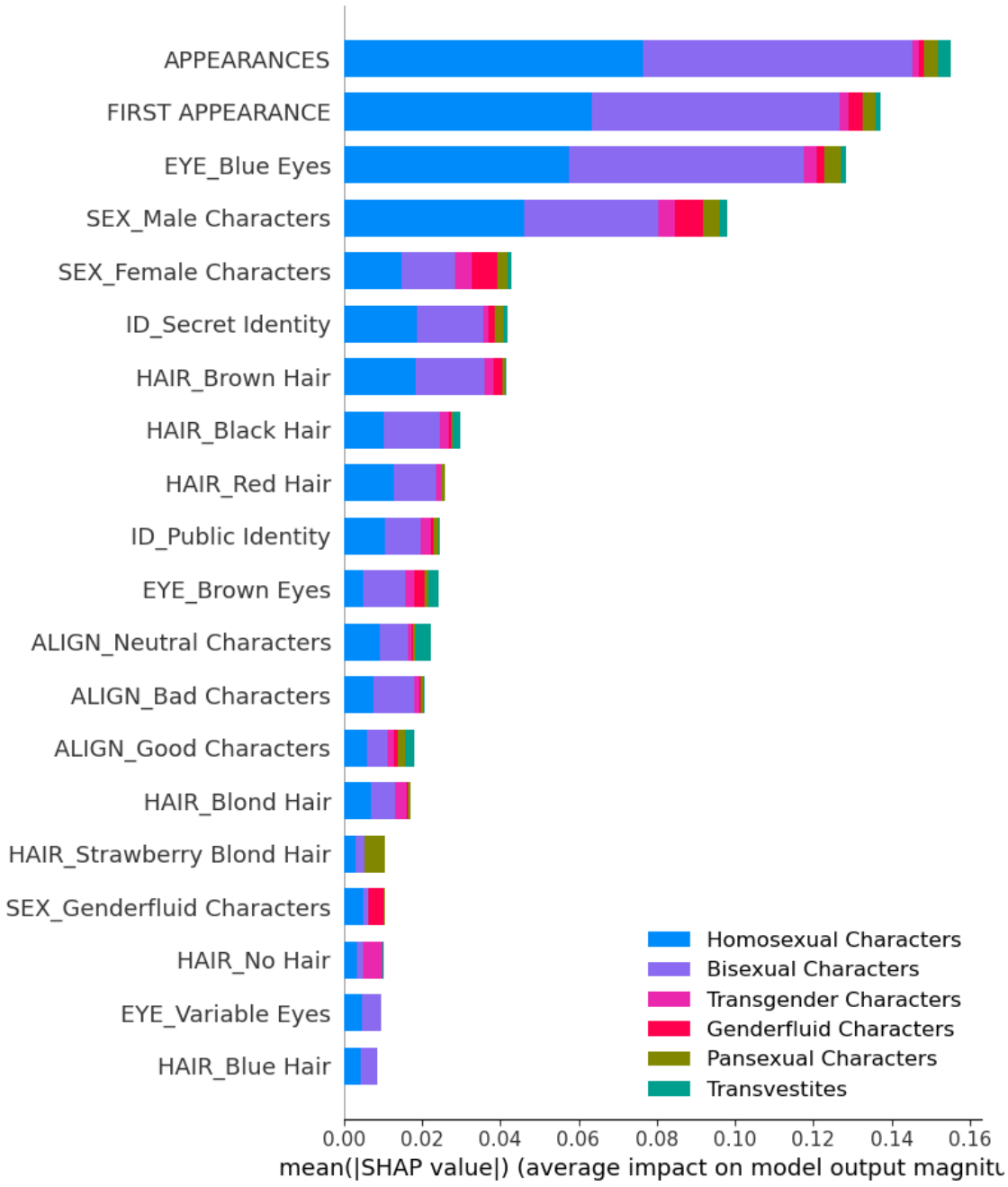

```
Created Waterfall plot for Combined EYE predictions
Creating Summary plot for Combined HAIR predictions
```



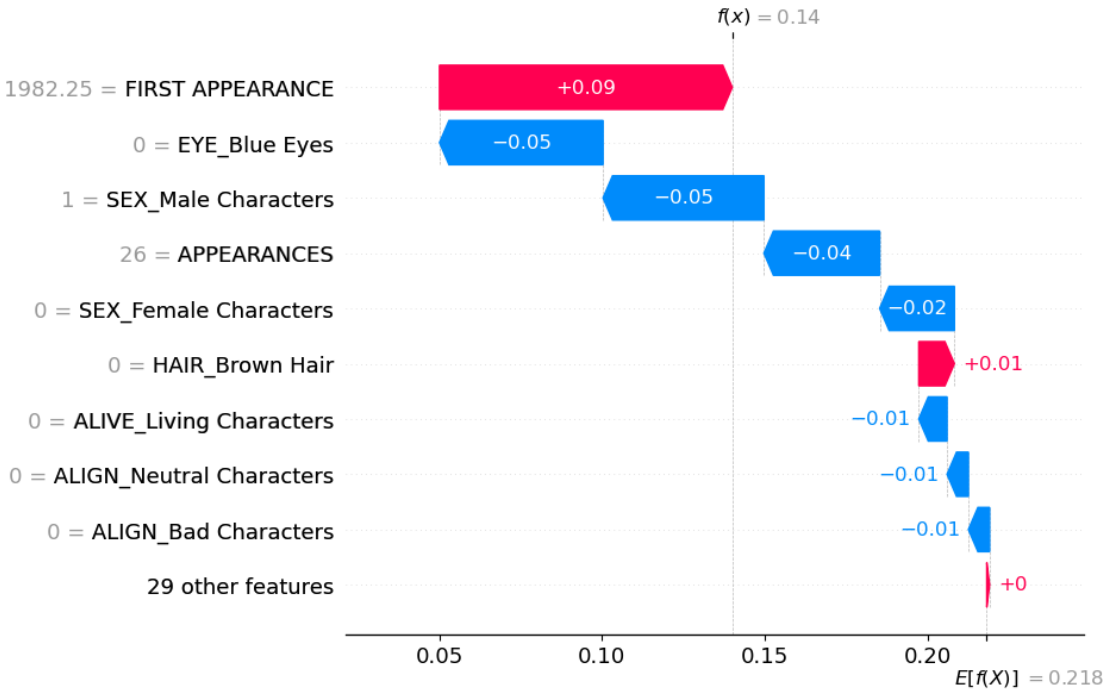

```
Created Summary plot for Combined HAIR predictions
Creating Waterfall plot for Combined HAIR predictions
```



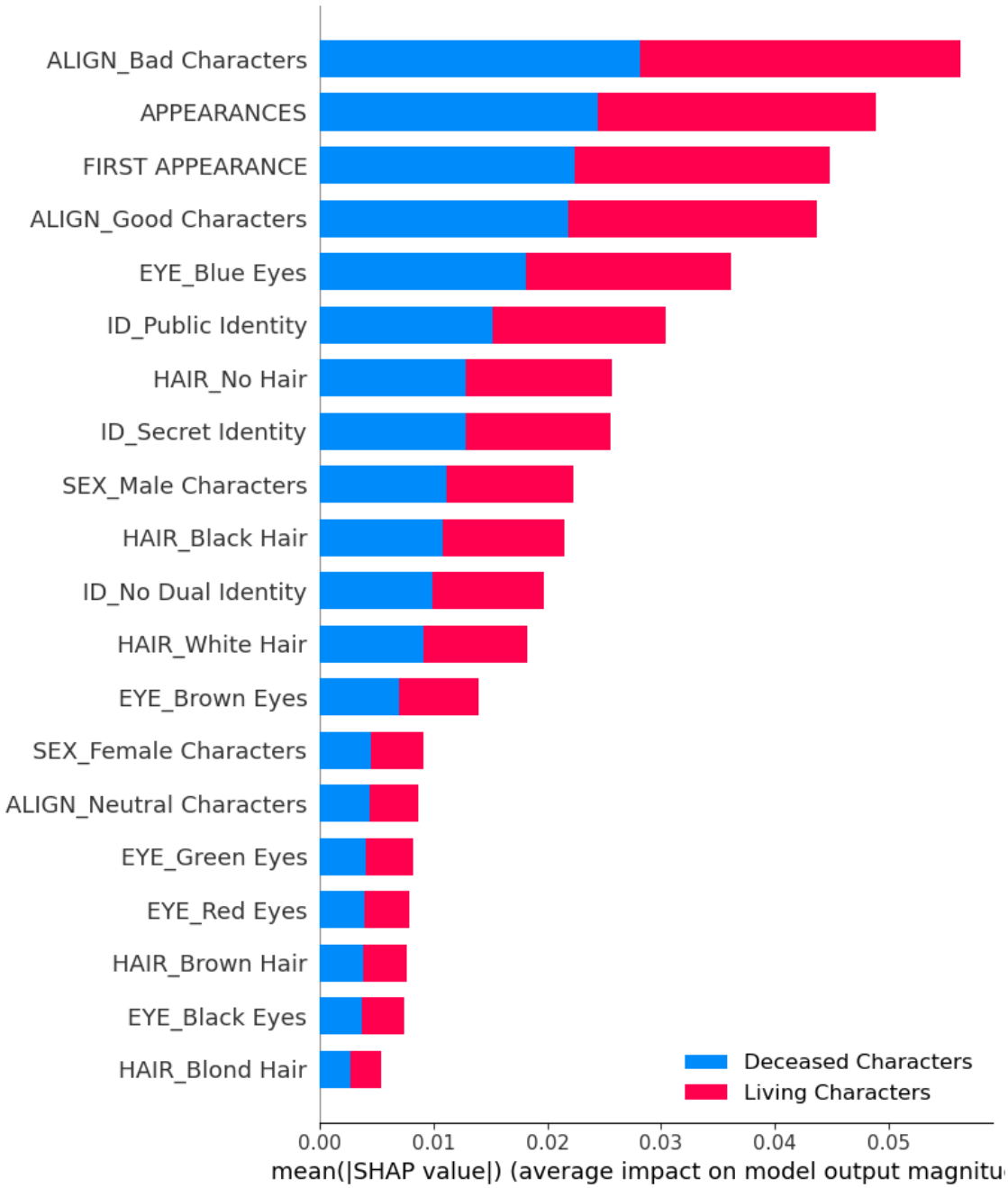

```
Created Waterfall plot for Combined HAIR predictions
Creating Summary plot for Combined GSM predictions
```



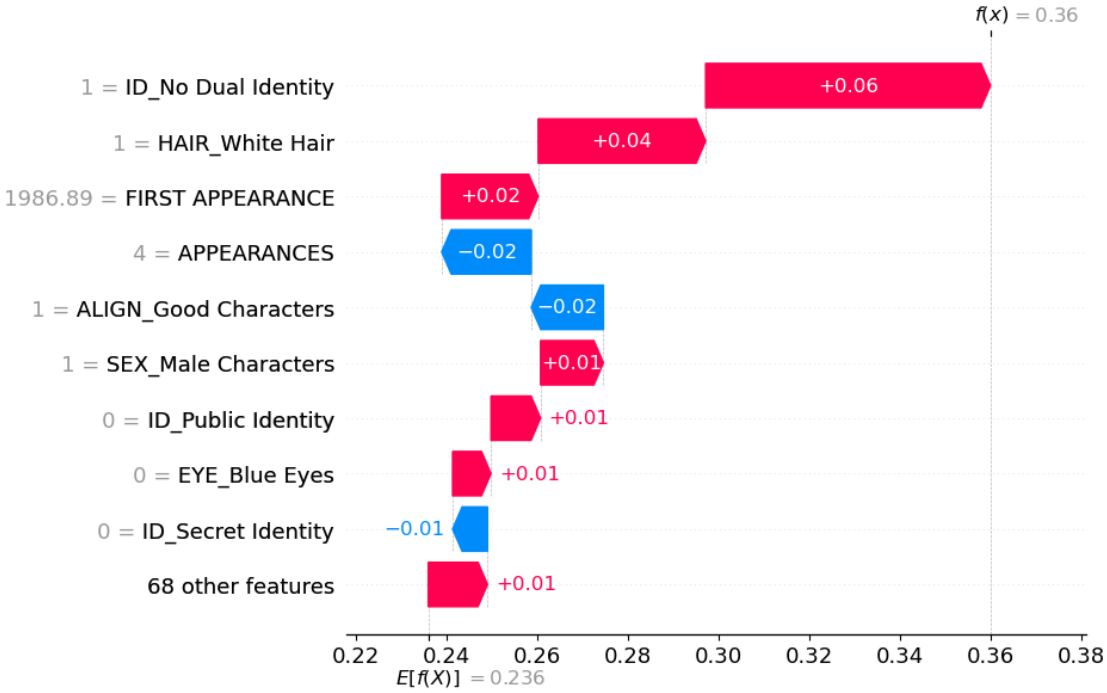

```
Created Summary plot for Combined GSM predictions
Creating Waterfall plot for Combined GSM predictions
```



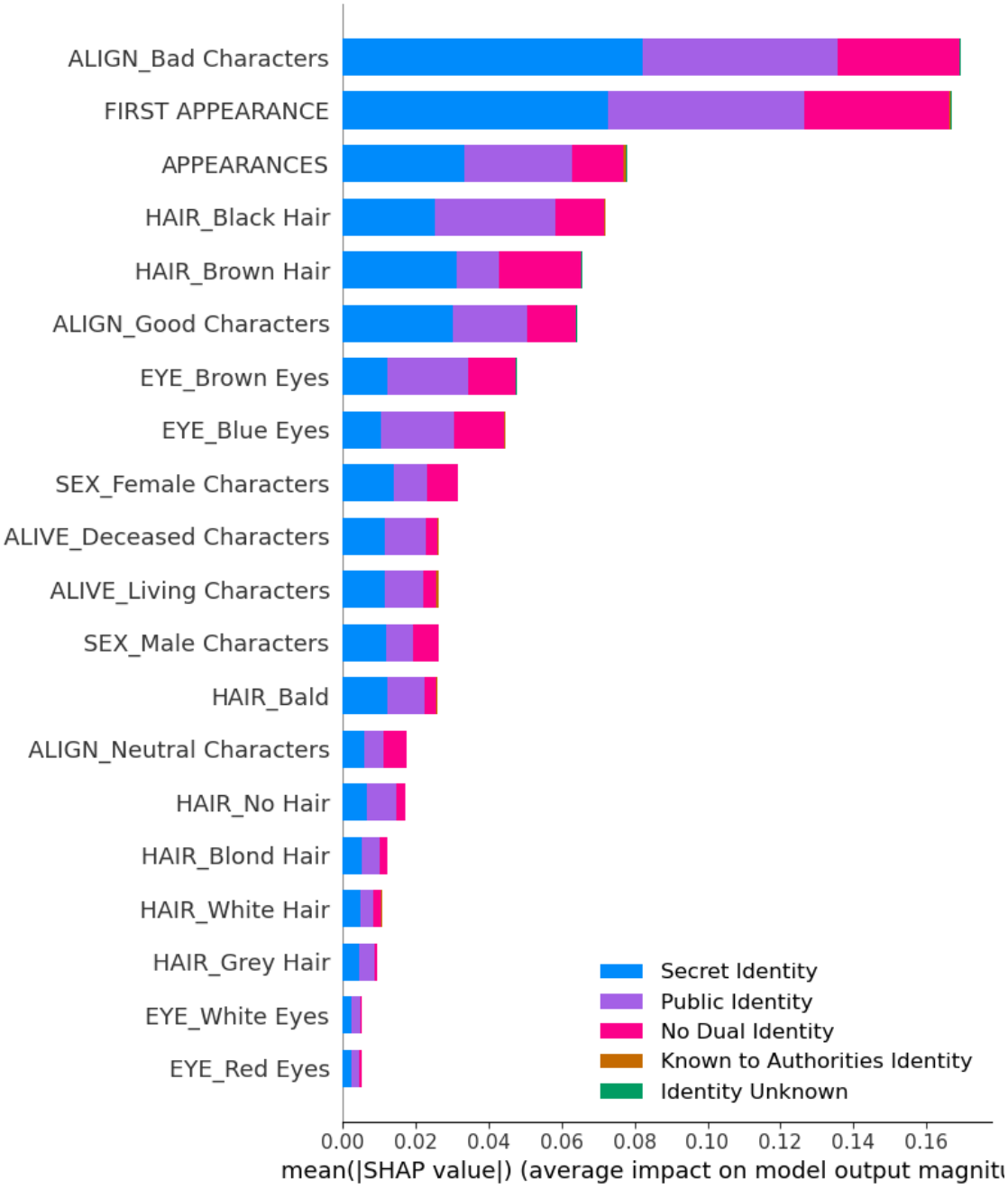

```
Created Waterfall plot for Combined GSM predictions
Creating Summary plot for Combined ALIVE predictions
```



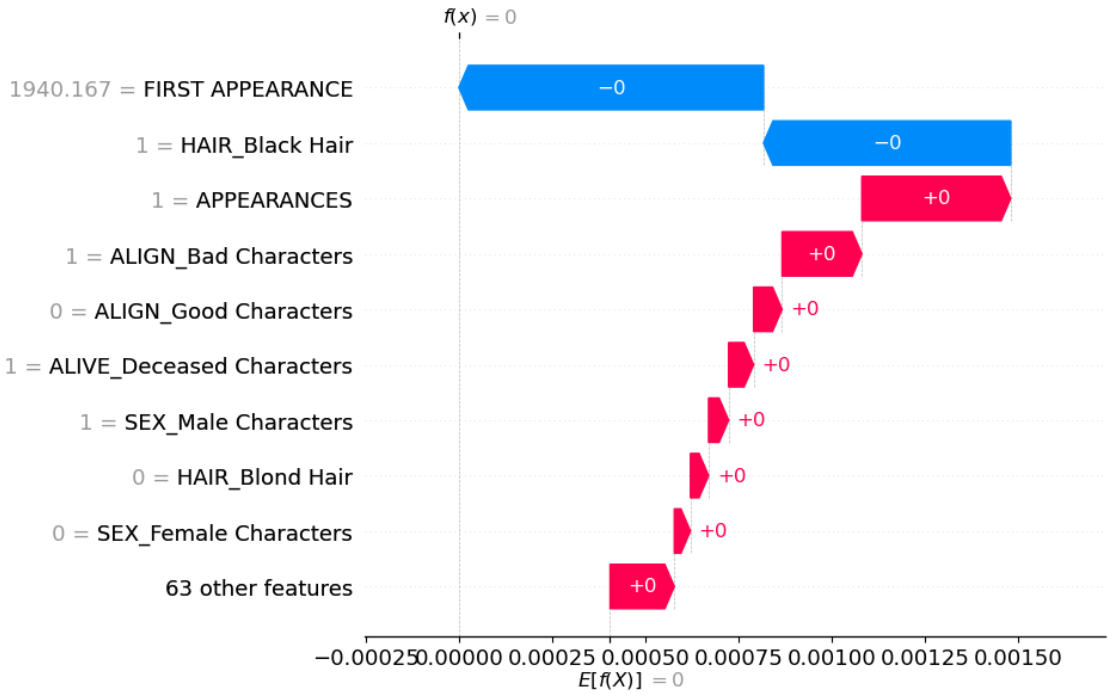

```
Created Summary plot for Combined ALIVE predictions
Creating Waterfall plot for Combined ALIVE predictions
```




```
Created Waterfall plot for Combined ALIVE predictions
Creating Summary plot for Combined ID predictions
```




```
Created Summary plot for Combined ID predictions
Creating Waterfall plot for Combined ID predictions
```

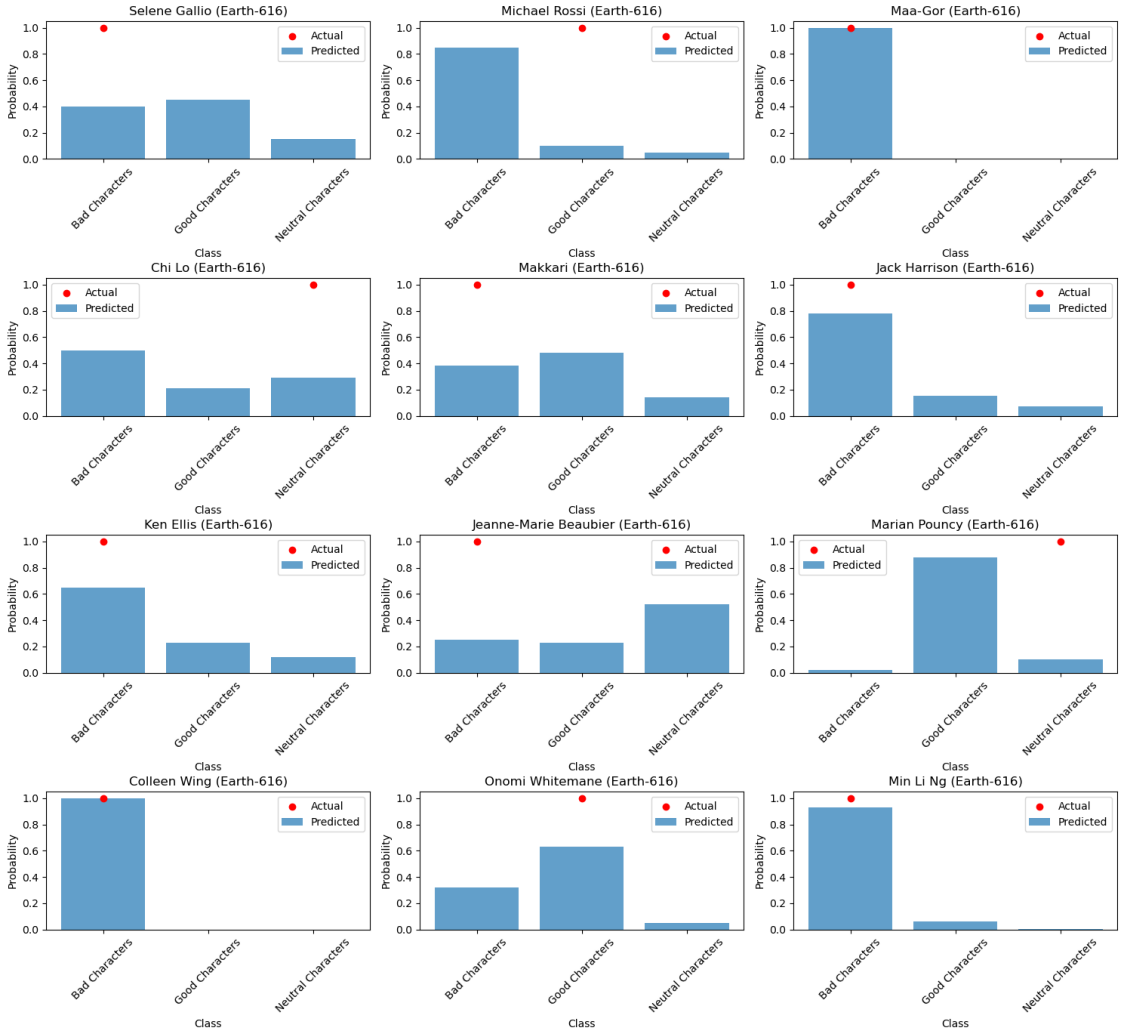


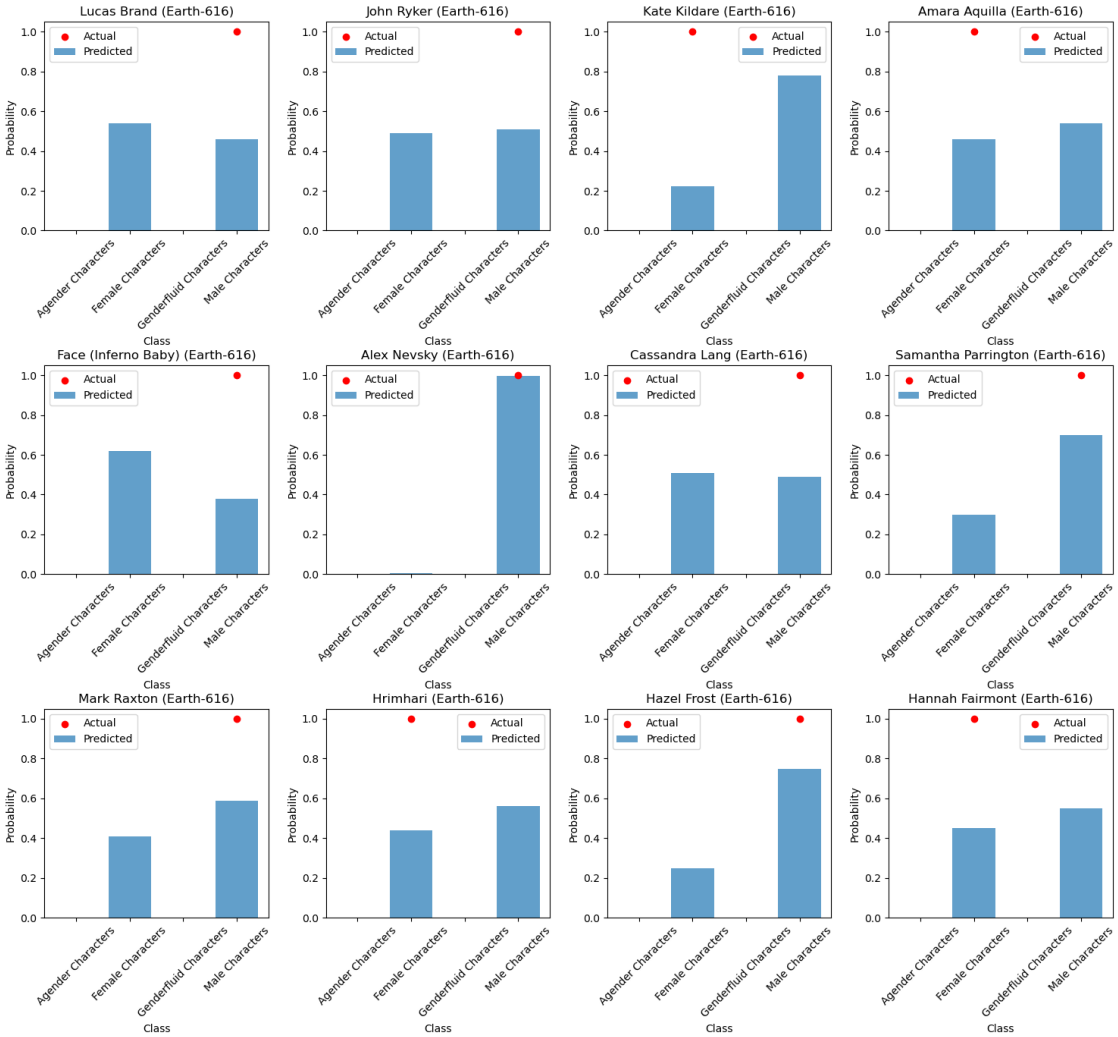

```
Created Waterfall plot for Combined ID predictions
Combined plots created
```

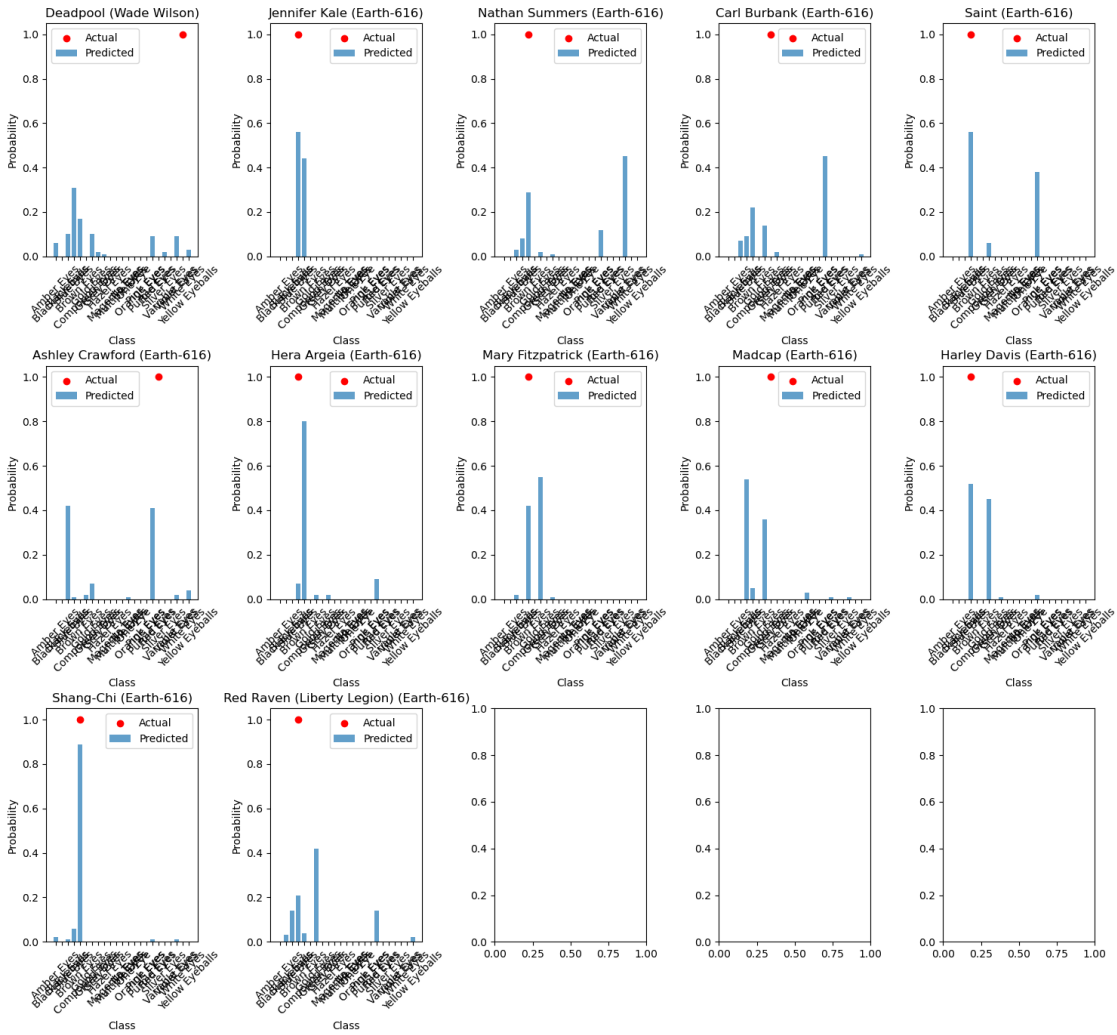
[ ]:
```
import math

# Loop through each dataset
for rf_model, X_train, y_train, X_test, y_test, target_feature, class_names in␣
↪rf_models_marvel:
    # Select a random subset of instances from the test data
    num_instances = min((int(len(X_test) * 0.1) if len(X_test) > 250 else␣
↪len(X_test)), 12)
    selected_indices = np.random.choice(len(X_test), num_instances,␣
↪replace=False)
    X_test_subset = X_test.iloc[selected_indices]
    y_test_subset = y_test[selected_indices]

    # Get the predicted probabilities for the selected instances in the test␣
↪data
    predicted_probabilities = rf_model.predict_proba(X_test_subset)

    # Get the subset of class names corresponding to the number of classes
    subset_class_names = class_names[:predicted_probabilities.shape[1]]

    # Calculate the number of rows and columns for subplots
```

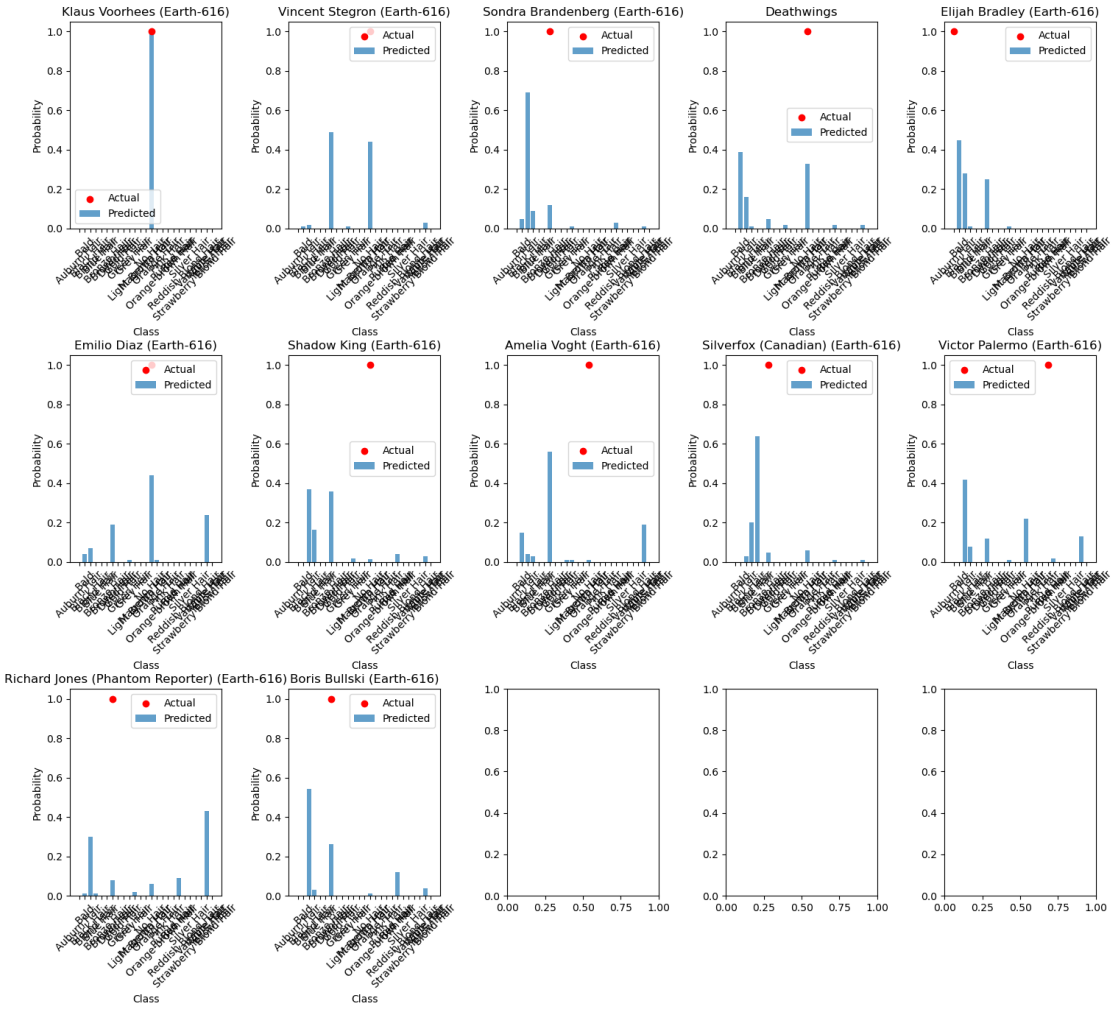
```
    num_instances_subset, num_classes = predicted_probabilities.shape
    num_columns = min(num_classes, 5)  # Limit the number of columns to avoid␣
↪too many subplots
    num_rows = math.ceil(num_instances_subset / num_columns)

    # Create a larger plot with subplots
    fig, axes = plt.subplots(num_rows, num_columns, figsize=(15, 15))
    fig.suptitle(f"Predicted Probabilities for {target_feature}", fontsize=16)

    # Loop through each instance and its corresponding predicted probabilities
    for i, (probs, ax) in enumerate(zip(predicted_probabilities, axes.
↪flatten())):
        character_name = str(marvel_names[selected_indices[i]])  # Convert to␣
↪string
        actual_class = y_test_subset[i]  # Get the actual class value

        # Plot the predicted probabilities as a bar chart
        ax.bar(subset_class_names, probs, label="Predicted", alpha=0.7)

        # Plot the actual class value as a point on top of the predicted␣
↪probabilities
        ax.scatter(actual_class, 1, color="red", label="Actual")

        ax.set_title(character_name)  # Set character name as the title
        ax.set_xlabel("Class")
        ax.set_ylabel("Probability")
        ax.set_xticks(range(len(subset_class_names)))  # Set tick positions
        ax.set_xticklabels(subset_class_names, rotation=45)  # Set tick labels
        ax.legend()  # Show legend

    # Adjust layout and display the plot
    plt.tight_layout()
    plt.subplots_adjust(top=0.9)
    plt.savefig(f"""figs/prob_charts/
↪Marvel_{target_feature}_{selected_indices}_probabilities.png""")
    plt.show()
```

Predicted Probabilities for ALIGN

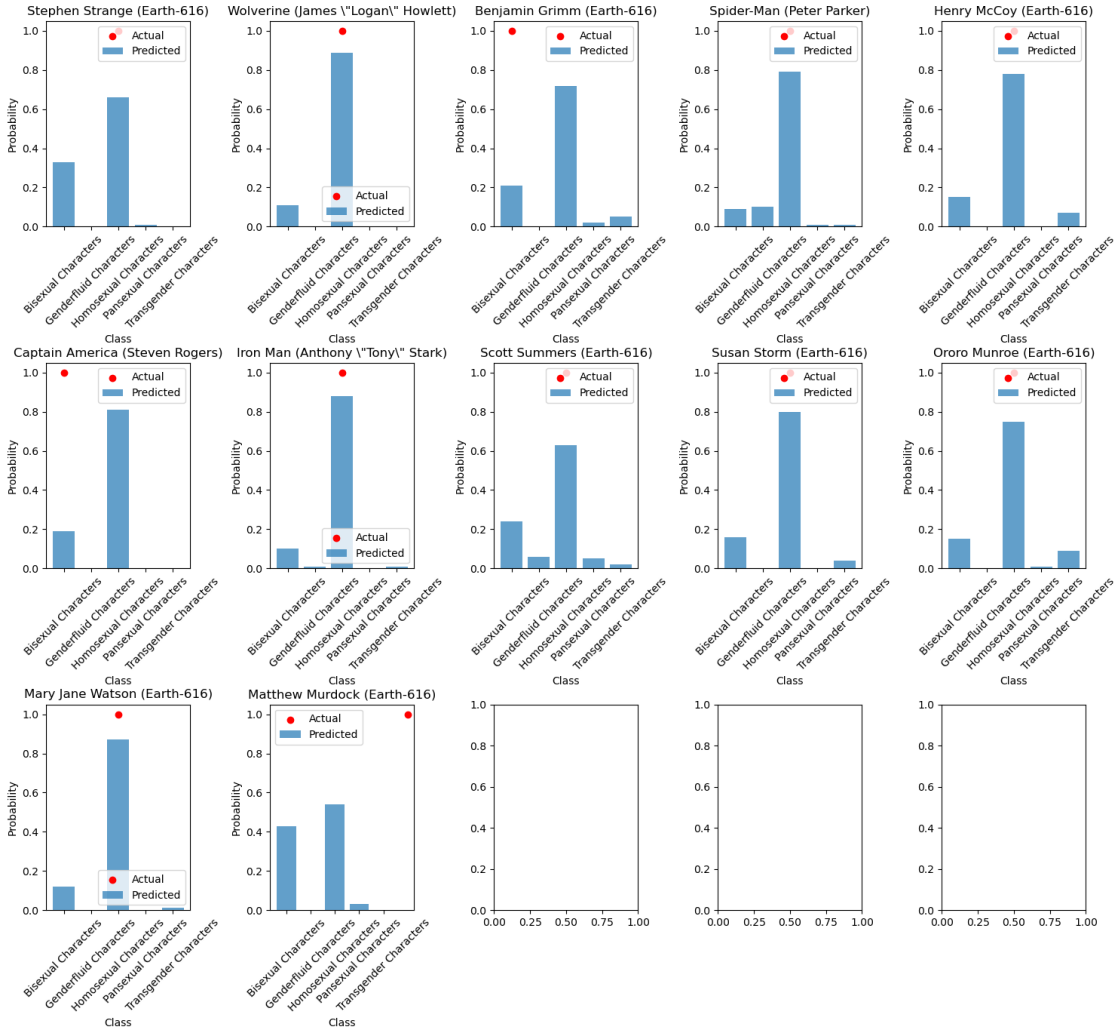



Predicted Probabilities for SEX
Lucas Brand (Earth-616)
John Ryker (Earth-616)
Kate Kildare (Earth-616)
Amara Aquilla (Earth-616)
Face (Inferno Baby) (Earth-616)
Alex Nevsky (Earth-616)
Cassandra Lang (Earth-616)
Samantha Parrington (Earth-616)
Mark Raxton (Earth-616)
Hrimhari (Earth-616)
Hazel Frost (Earth-616)
Hannah Fairmont (Earth-616)
Actual
Predicted
Probability
Class
Agender Characters
Female Characters
Genderfluid Characters
Male Characters

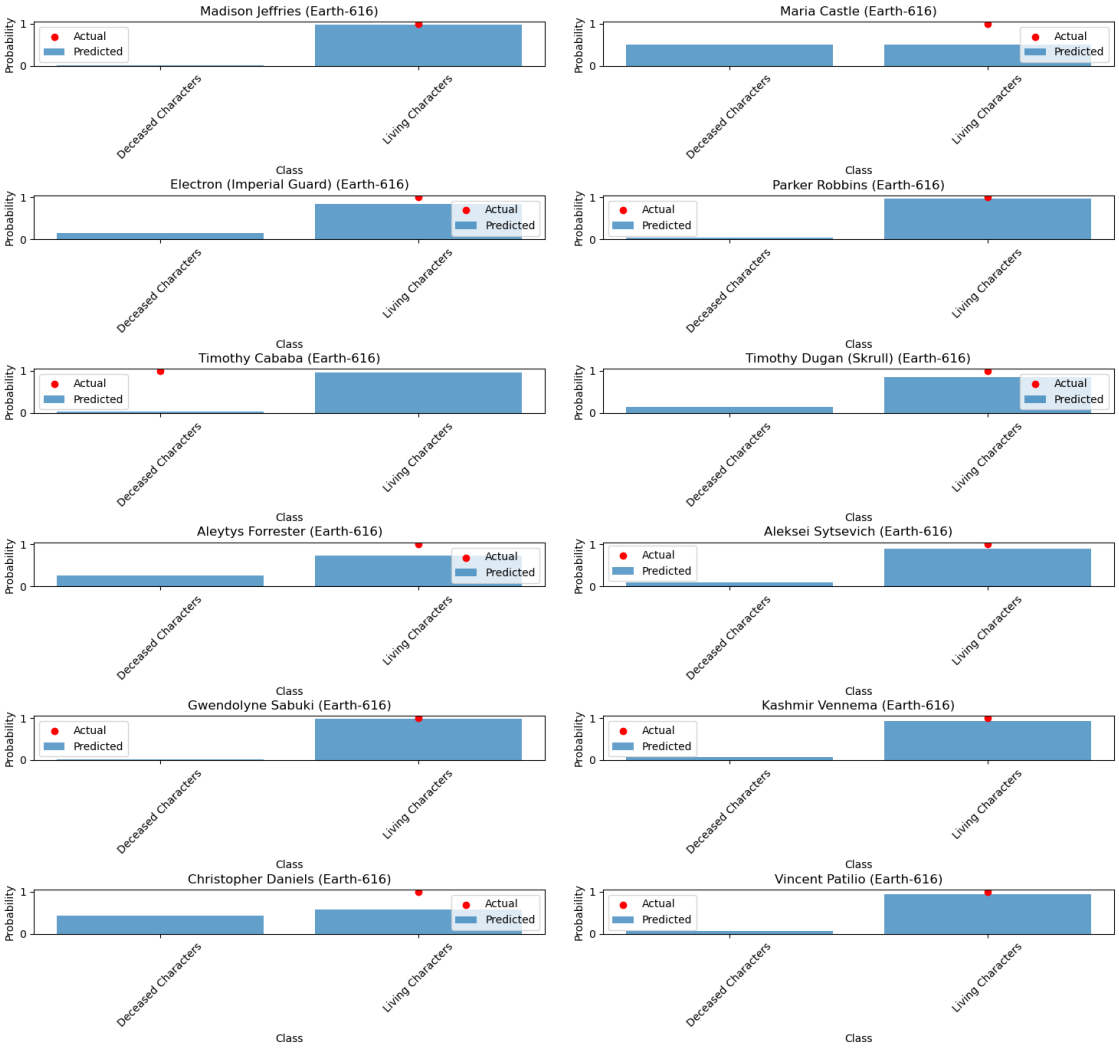

Predicted Probabilities for EYE
Deadpool (Wade Wilson)
Jennifer Kale (Earth-616)
Nathan Summers (Earth-616)
Carl Burbank (Earth-616)
Saint (Earth-616)
Ashley Crawford (Earth-616)
Hera Argeia (Earth-616)
Mary Fitzpatrick (Earth-616)
Madcap (Earth-616)
Harley Davis (Earth-616)
Shang-Chi (Earth-616)
Red Raven (Liberty Legion) (Earth-616)
Actual
Predicted
Probability
Class

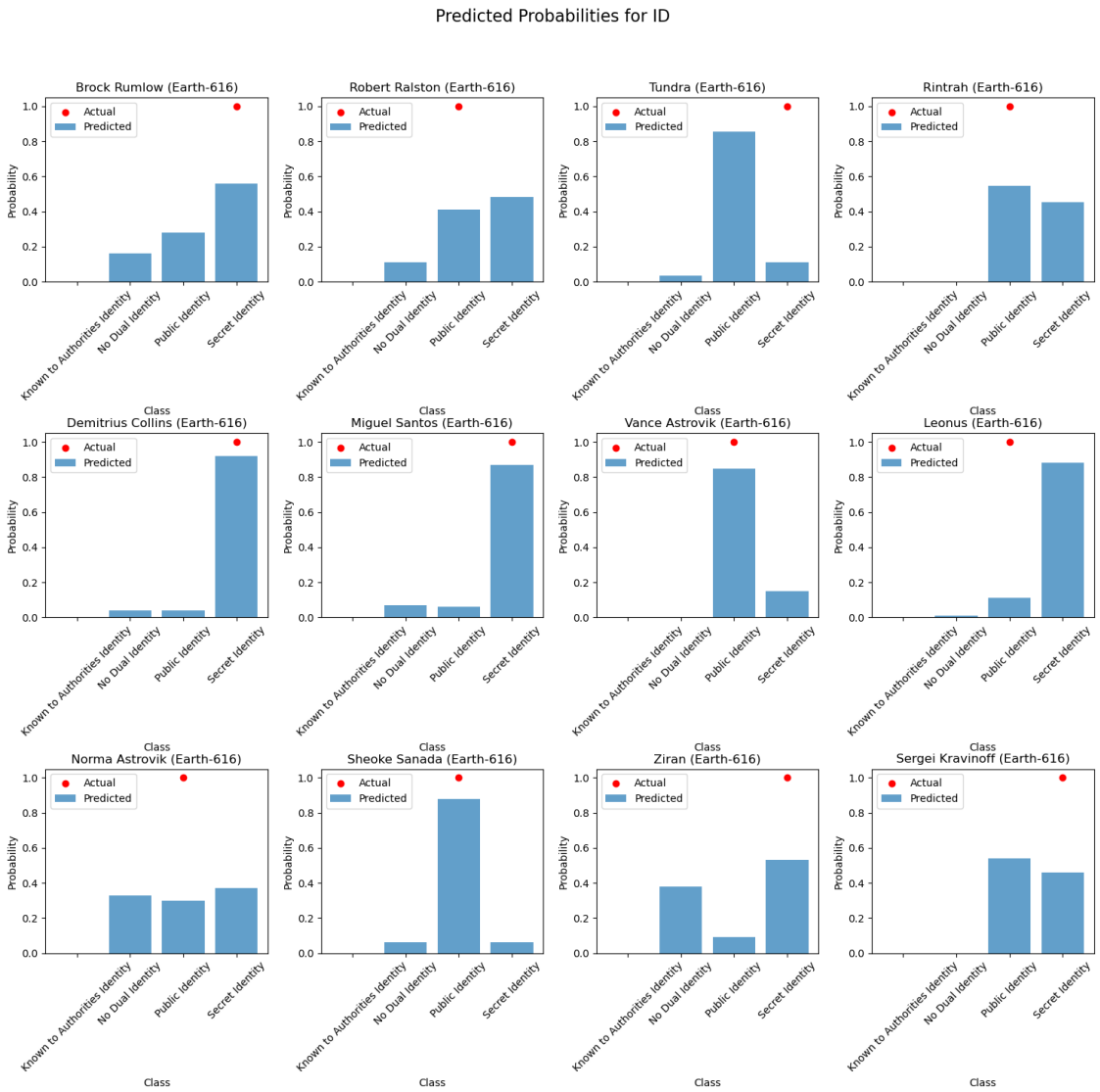

Predicted Probabilities for HAIR
Klaus Voorhees (Earth-616)
Vincent Stegron (Earth-616)
Sondra Brandenberg (Earth-616)
Deathwings
Elijah Bradley (Earth-616)
Emilio Diaz (Earth-616)
Shadow King (Earth-616)
Amelia Voght (Earth-616)
Silverfox (Canadian) (Earth-616)
Victor Palermo (Earth-616)
Richard Jones (Phantom Reporter) (Earth-616)
Boris Bullski (Earth-616)
Actual
Predicted
Probability
Class

Predicted Probabilities for GSM



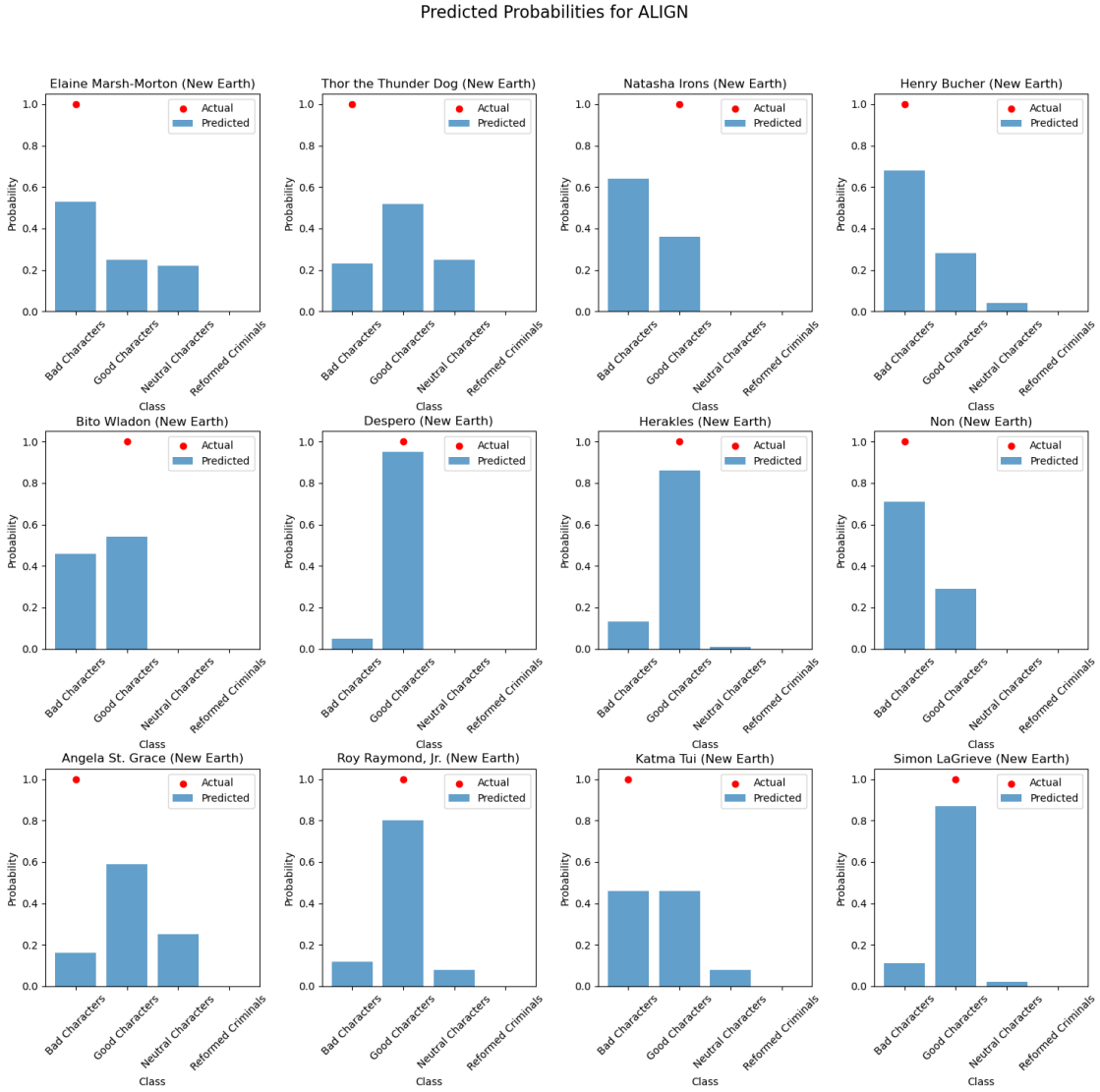
Predicted Probabilities for ALIVE



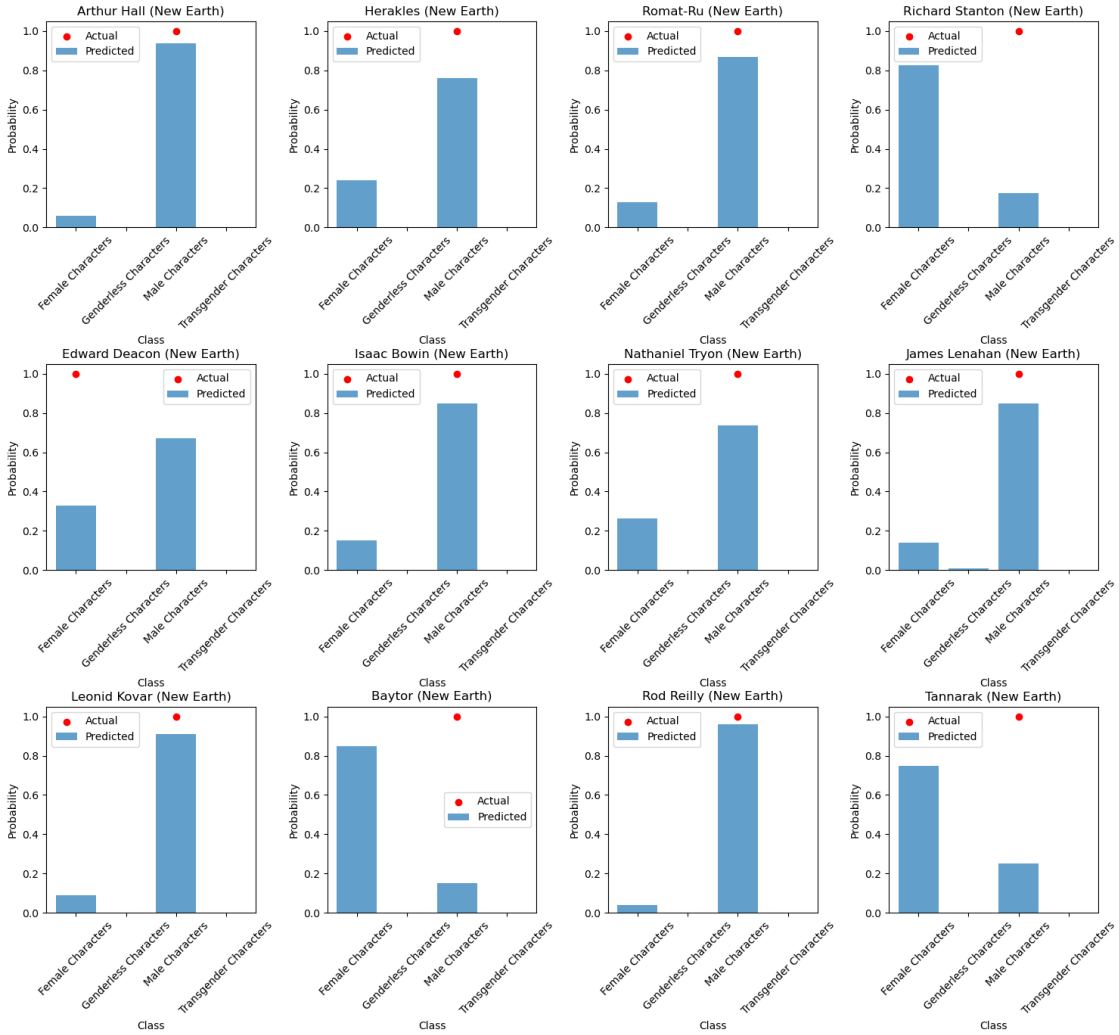


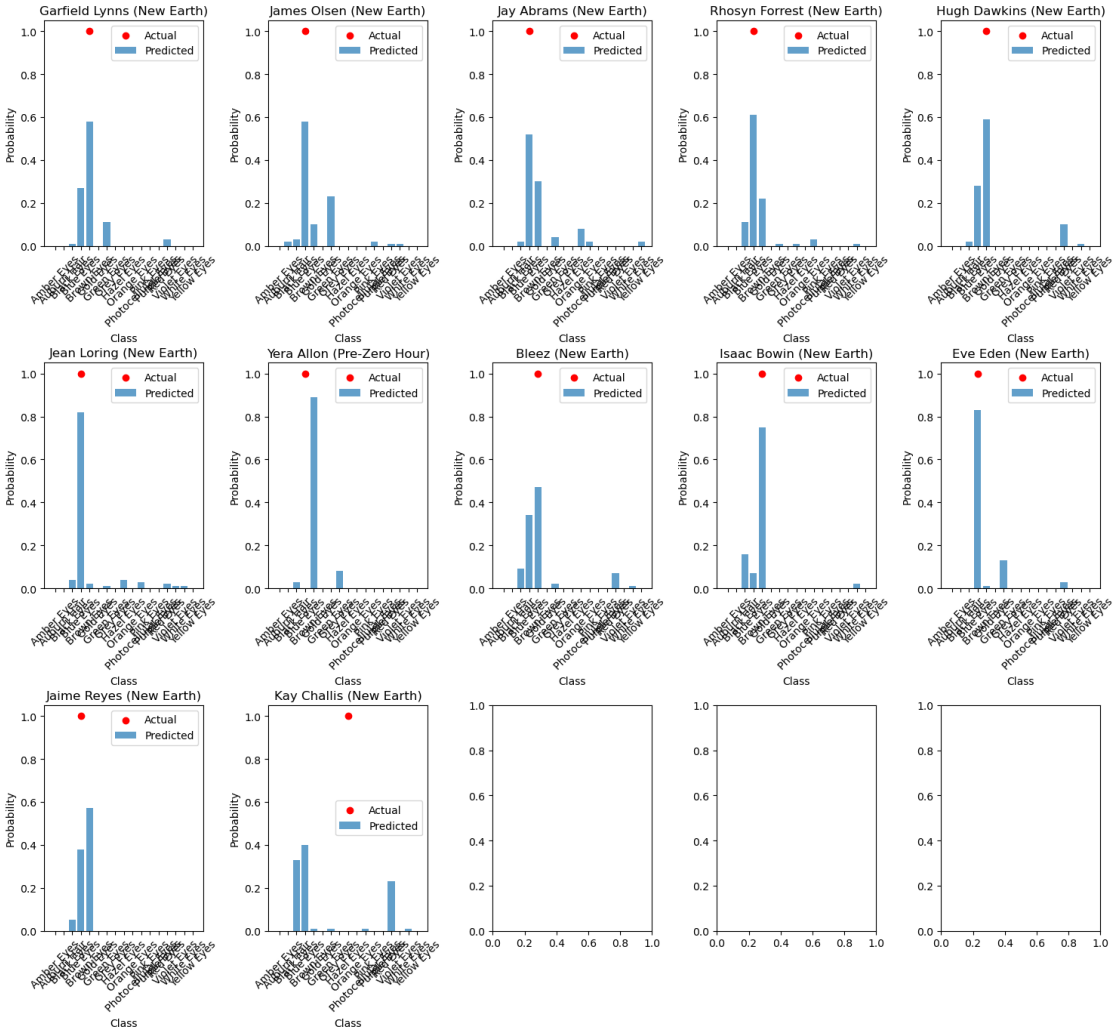
[ ]:
```
# Loop through each dataset
for rf_model, X_train, y_train, X_test, y_test, target_feature, class_names in␣
↪rf_models_dc:
    # Select a random subset of instances from the test data
    num_instances = min((int(len(X_test) * 0.1) if len(X_test) > 250 else␣
↪len(X_test)), 12)
    selected_indices = np.random.choice(len(X_test), num_instances,␣
↪replace=False)
    X_test_subset = X_test.iloc[selected_indices]
    y_test_subset = y_test[selected_indices]

    # Get the predicted probabilities for the selected instances in the test␣
↪data
```

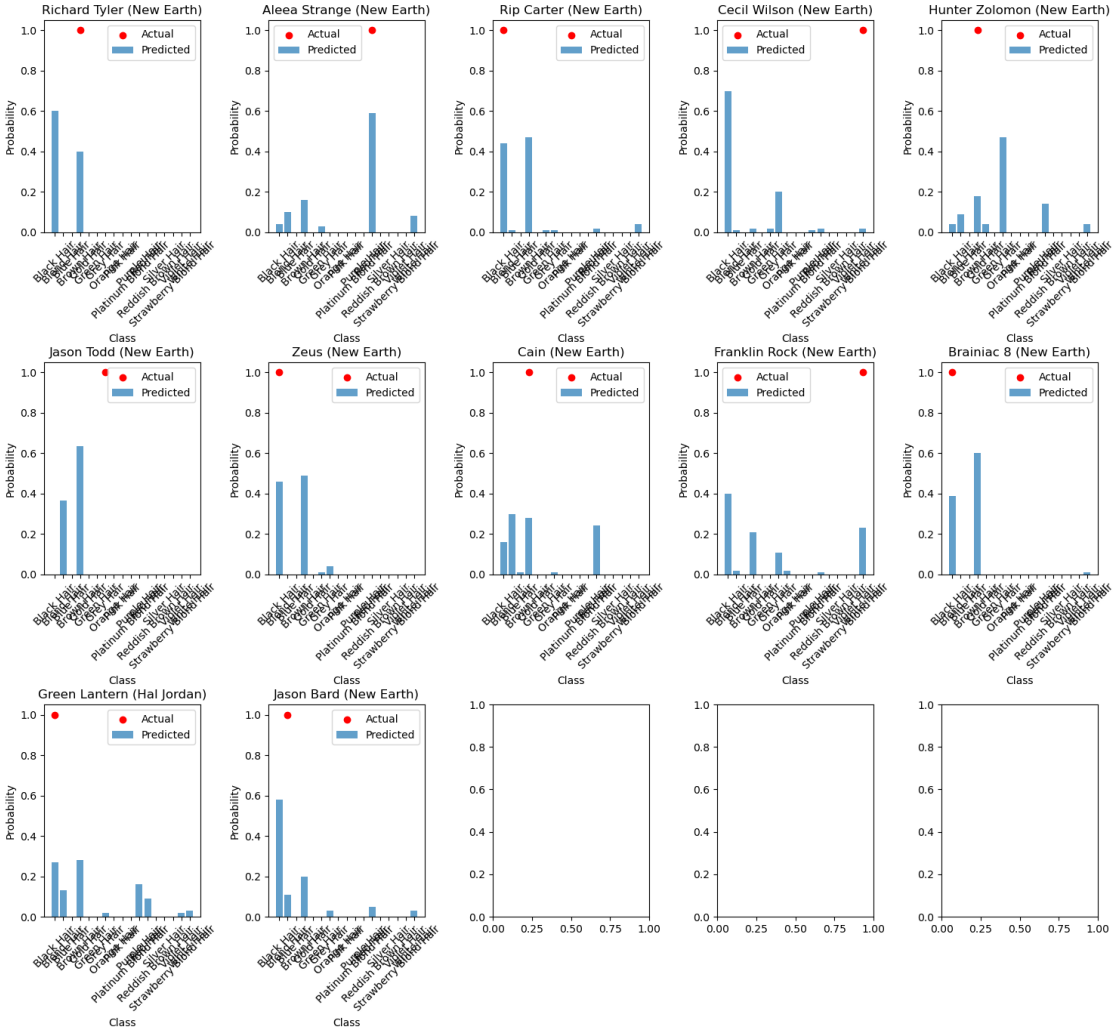
```
    predicted_probabilities = rf_model.predict_proba(X_test_subset)

    # Get the subset of class names corresponding to the number of classes
    subset_class_names = class_names[:predicted_probabilities.shape[1]]

    # Calculate the number of rows and columns for subplots
    num_instances_subset, num_classes = predicted_probabilities.shape
    num_columns = min(num_classes, 5)  # Limit the number of columns to avoid␣
↪too many subplots
    num_rows = math.ceil(num_instances_subset / num_columns)

    # Create a larger plot with subplots
    fig, axes = plt.subplots(num_rows, num_columns, figsize=(15, 15))
    fig.suptitle(f"Predicted Probabilities for {target_feature}", fontsize=16)

    # Loop through each instance and its corresponding predicted probabilities
    for i, (probs, ax) in enumerate(zip(predicted_probabilities, axes.
↪flatten())):
        character_name = str(dc_names[selected_indices[i]])  # Convert to string
        actual_class = y_test_subset[i]  # Get the actual class value

        # Plot the predicted probabilities as a bar chart
        ax.bar(subset_class_names, probs, label="Predicted", alpha=0.7)

        # Plot the actual class value as a point on top of the predicted␣
↪probabilities
        ax.scatter(actual_class, 1, color="red", label="Actual")

        ax.set_title(character_name)  # Set character name as the title
        ax.set_xlabel("Class")
        ax.set_ylabel("Probability")
        ax.set_xticks(range(len(subset_class_names)))  # Set tick positions
        ax.set_xticklabels(subset_class_names, rotation=45)  # Set tick labels
        ax.legend()  # Show legend

    # Adjust layout and display the plot
    plt.tight_layout()
    plt.subplots_adjust(top=0.9)
    plt.savefig(f"""figs/prob_charts/
↪DC_{target_feature}_{selected_indices}_probabilities.png""")
    plt.show()
```


Predicted Probabilities for ALIGN
Elaine Marsh-Morton (New Earth)
Thor the Thunder Dog (New Earth)
Natasha Irons (New Earth)
Henry Bucher (New Earth)
Bito Wladon (New Earth)
Despero (New Earth)
Herakles (New Earth)
Non (New Earth)
Angela St. Grace (New Earth)
Roy Raymond, Jr. (New Earth)
Katma Tui (New Earth)
Simon LaGrieve (New Earth)
Actual
Predicted
Probability
Class
Bad Characters
Good Characters
Neutral Characters
Reformed Criminals

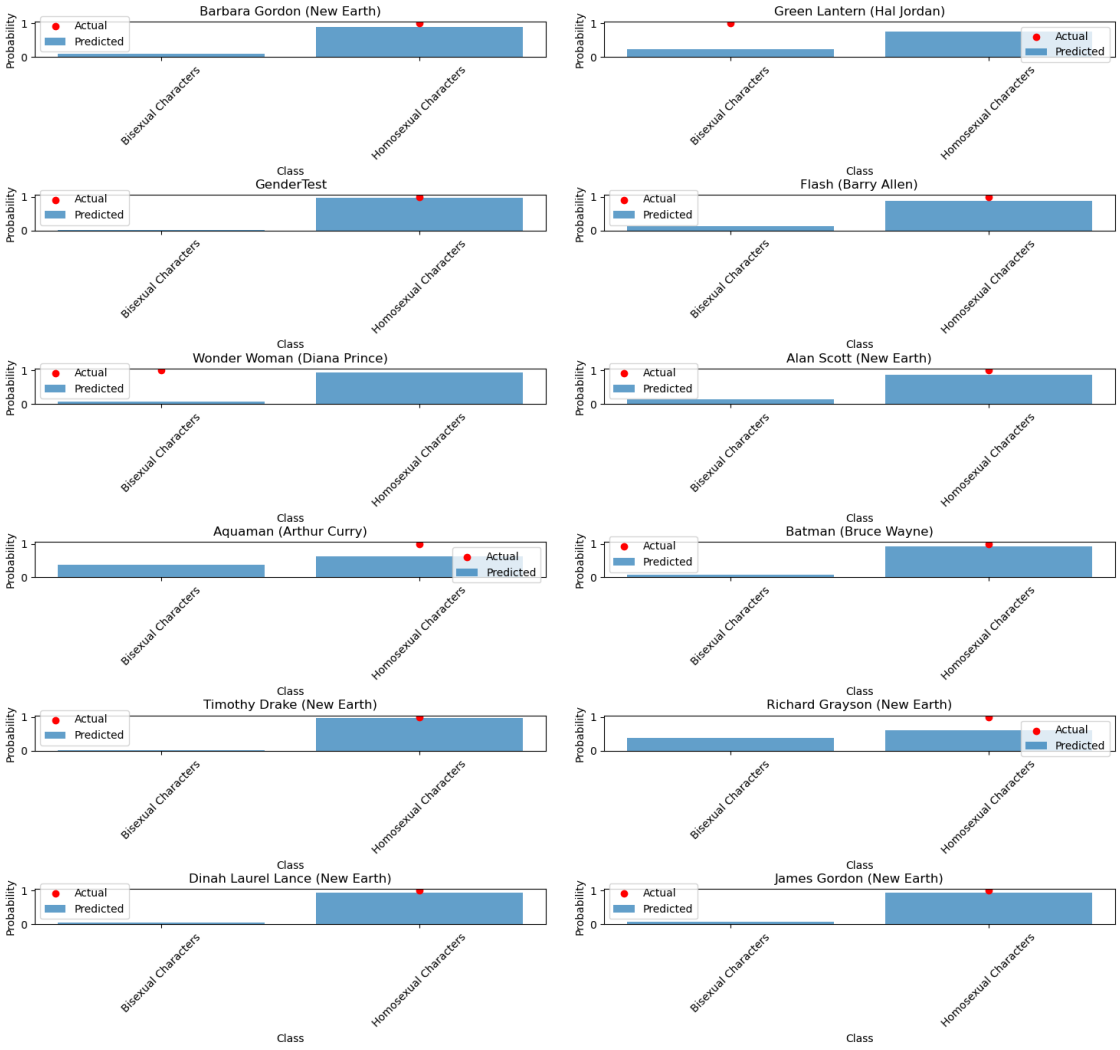
Predicted Probabilities for SEX

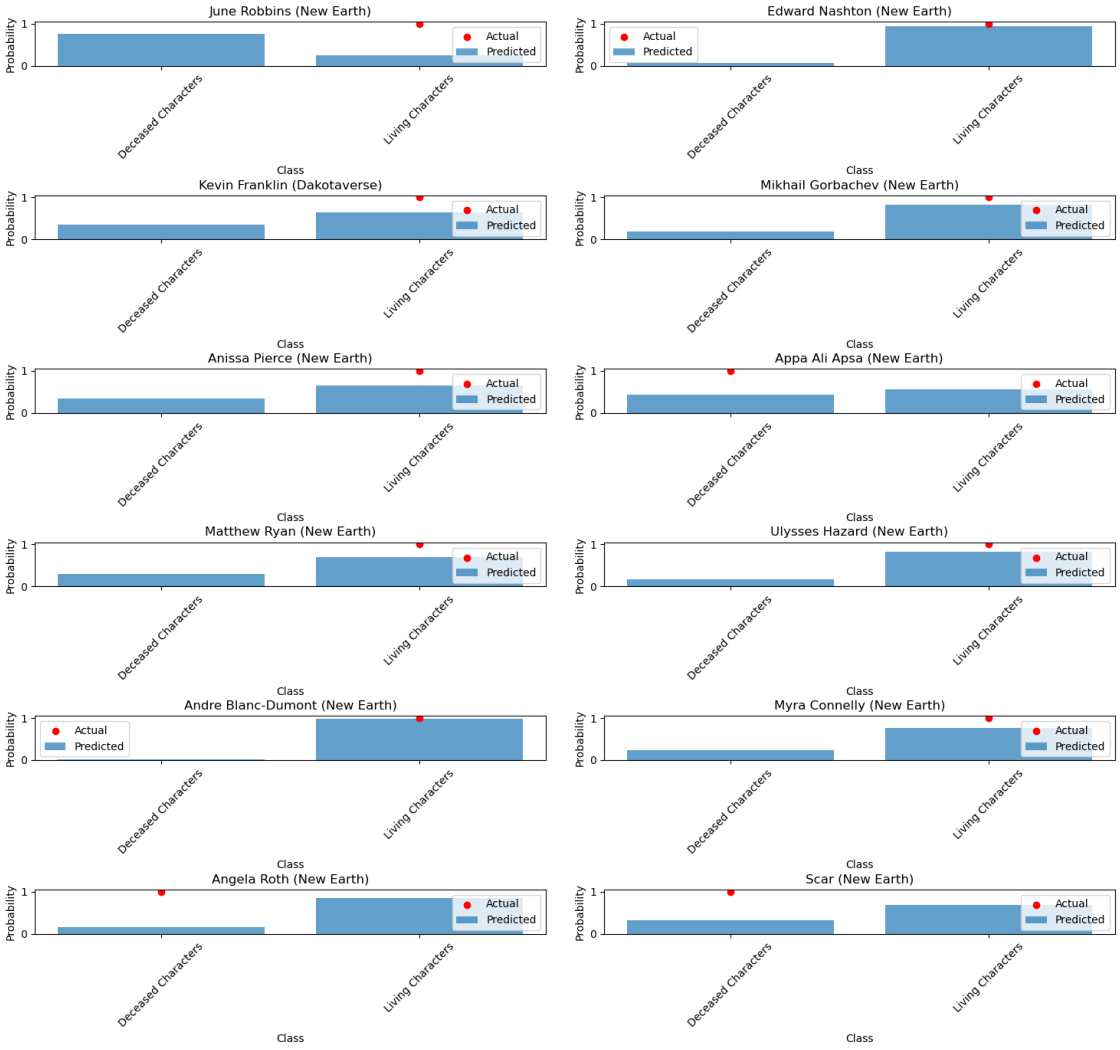


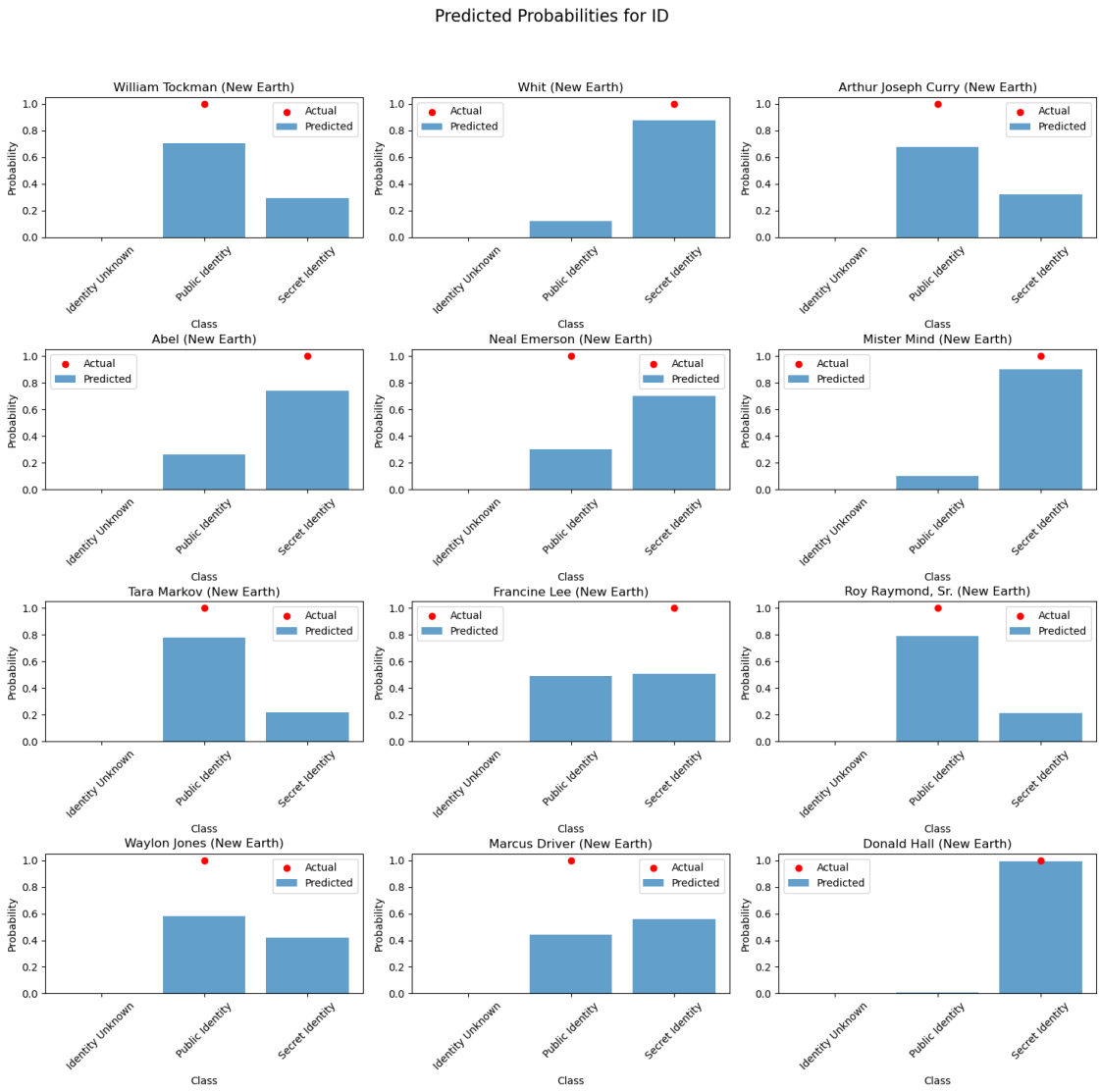

Predicted Probabilities for EYE
Garfield Lynns (New Earth)
James Olsen (New Earth)
Jay Abrams (New Earth)
Rhosyn Forrest (New Earth)
Hugh Dawkins (New Earth)
Jean Loring (New Earth)
Yera Allon (Pre-Zero Hour)
Bleez (New Earth)
Isaac Bowin (New Earth)
Eve Eden (New Earth)
Jaime Reyes (New Earth)
Kay Challis (New Earth)
Actual
Predicted
Probability
Class


Predicted Probabilities for HAIR
Richard Tyler (New Earth)
Aleea Strange (New Earth)
Rip Carter (New Earth)
Cecil Wilson (New Earth)
Hunter Zolomon (New Earth)
Jason Todd (New Earth)
Zeus (New Earth)
Cain (New Earth)
Franklin Rock (New Earth)
Brainiac 8 (New Earth)
Green Lantern (Hal Jordan)
Jason Bard (New Earth)
Actual
Predicted
Probability
Class

Predicted Probabilities for GSM

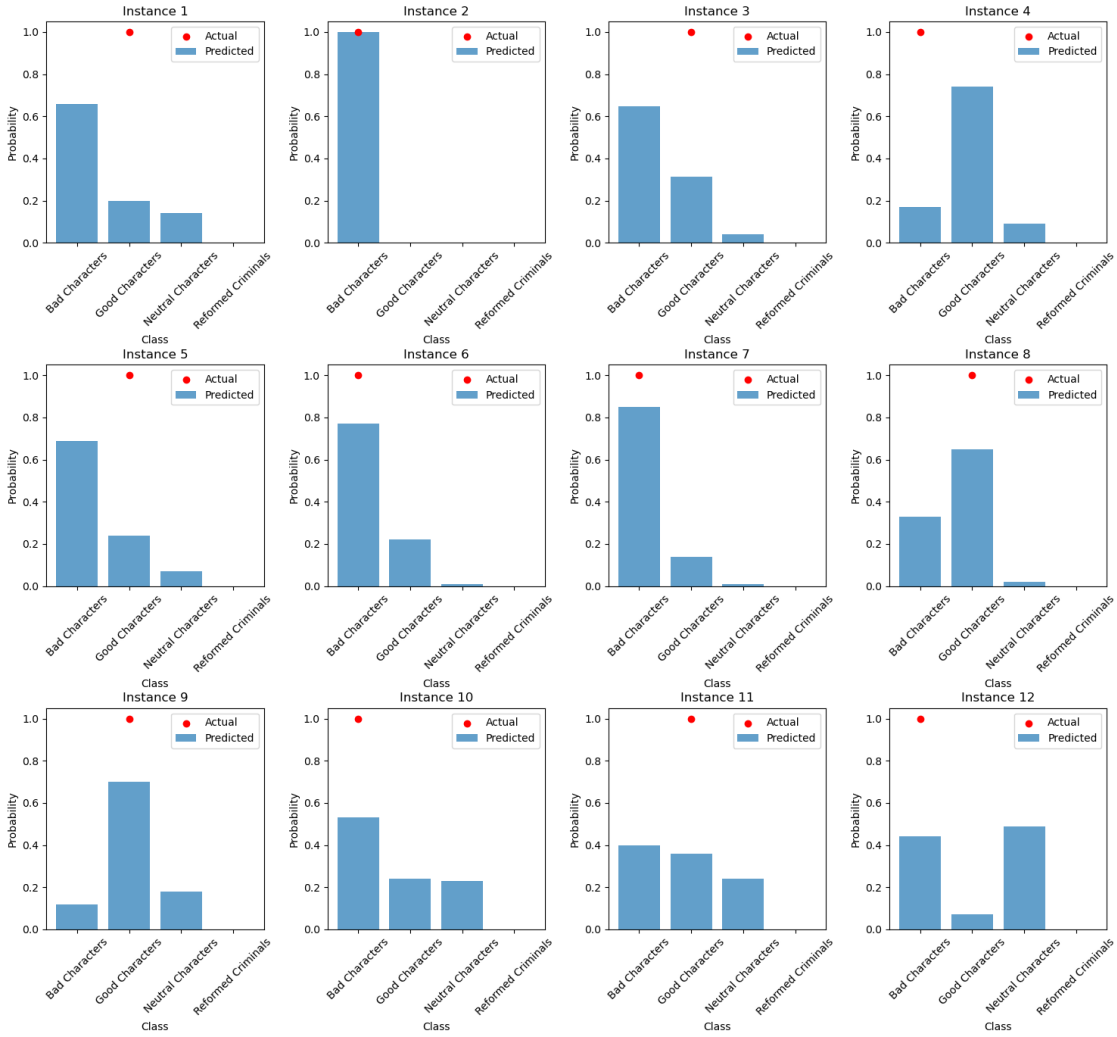


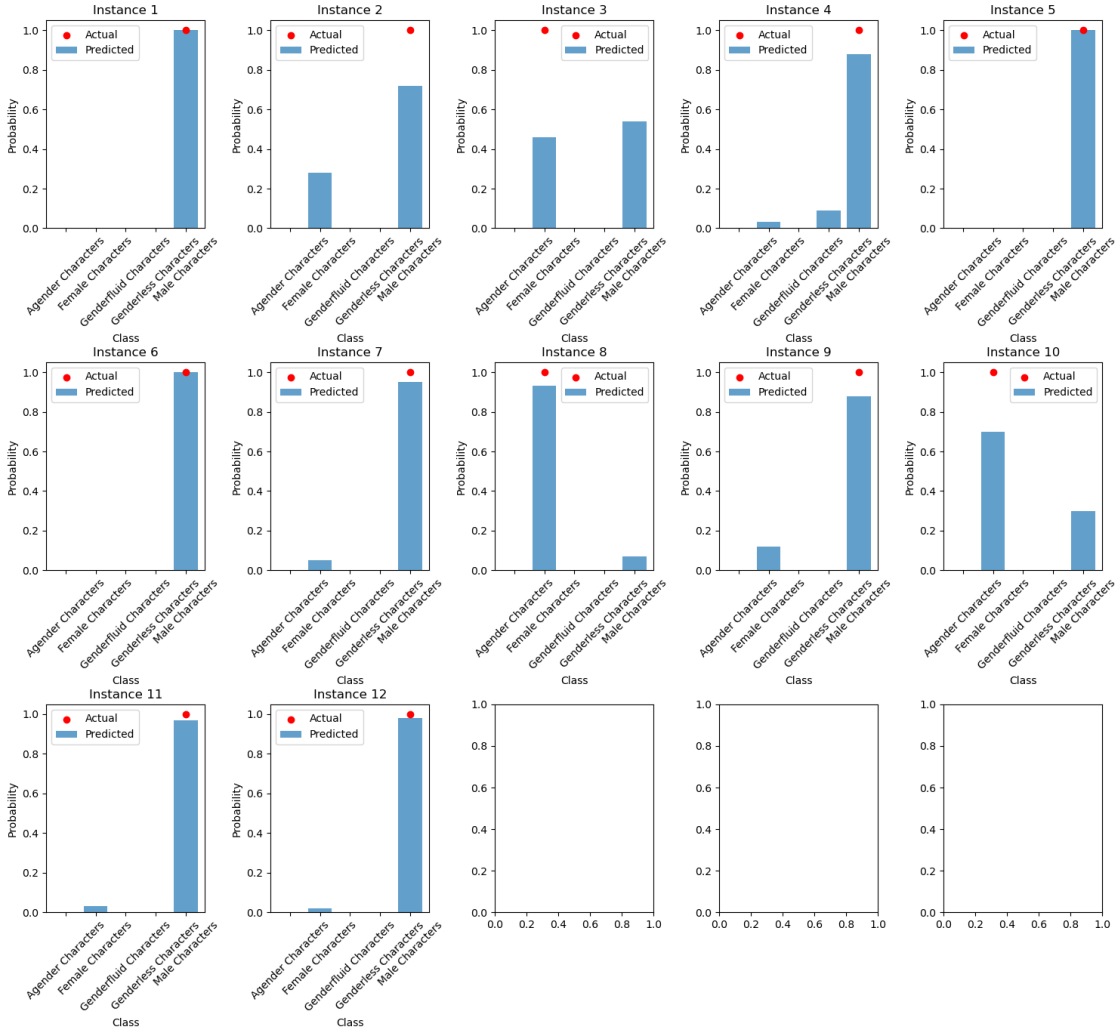

Predicted Probabilities for ALIVE
June Robbins (New Earth)
Edward Nashton (New Earth)
Kevin Franklin (Dakotaverse)
Mikhail Gorbachev (New Earth)
Anissa Pierce (New Earth)
Appa Ali Apsa (New Earth)
Matthew Ryan (New Earth)
Ulysses Hazard (New Earth)
Andre Blanc-Dumont (New Earth)
Myra Connelly (New Earth)
Angela Roth (New Earth)
Scar (New Earth)
Probability
Class
Deceased Characters
Living Characters
Actual
Predicted

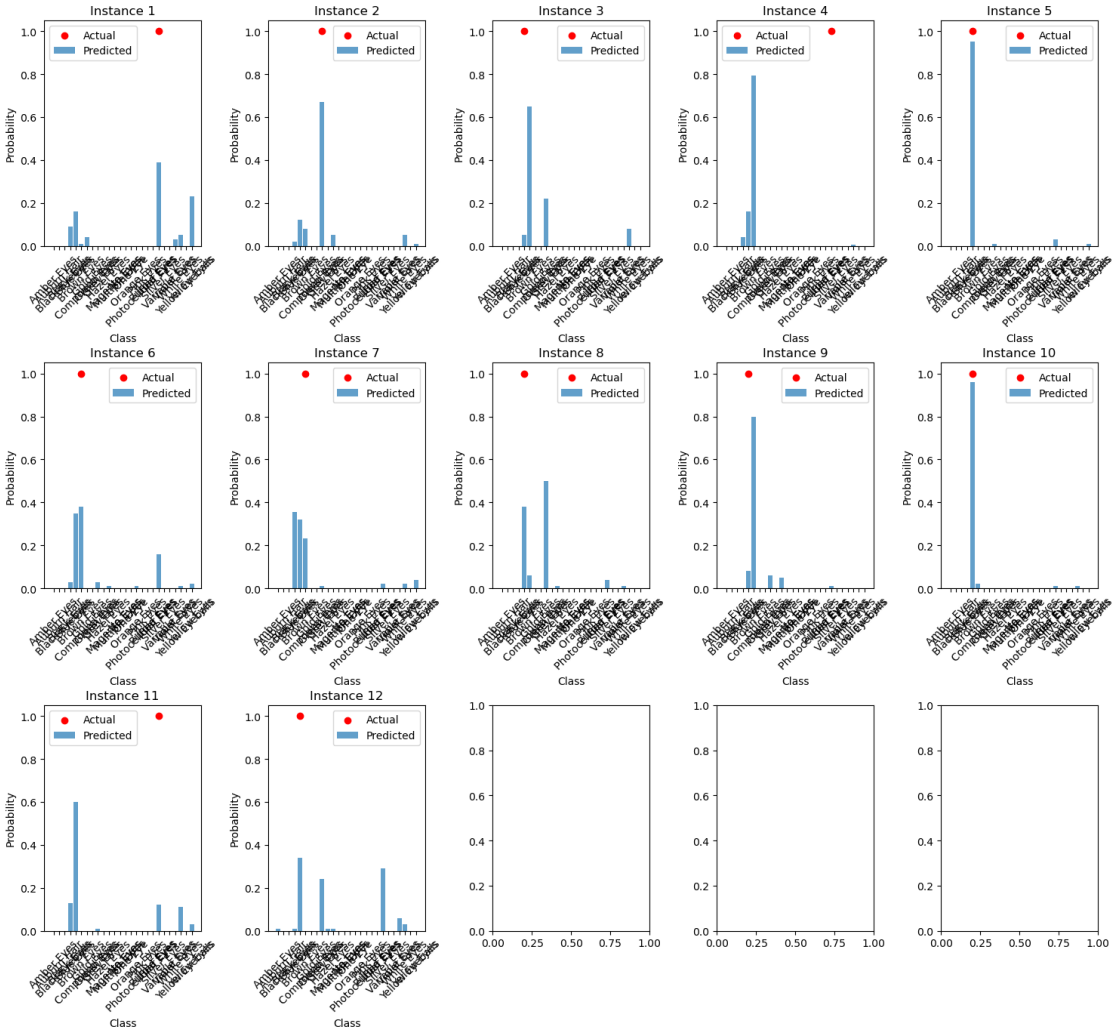


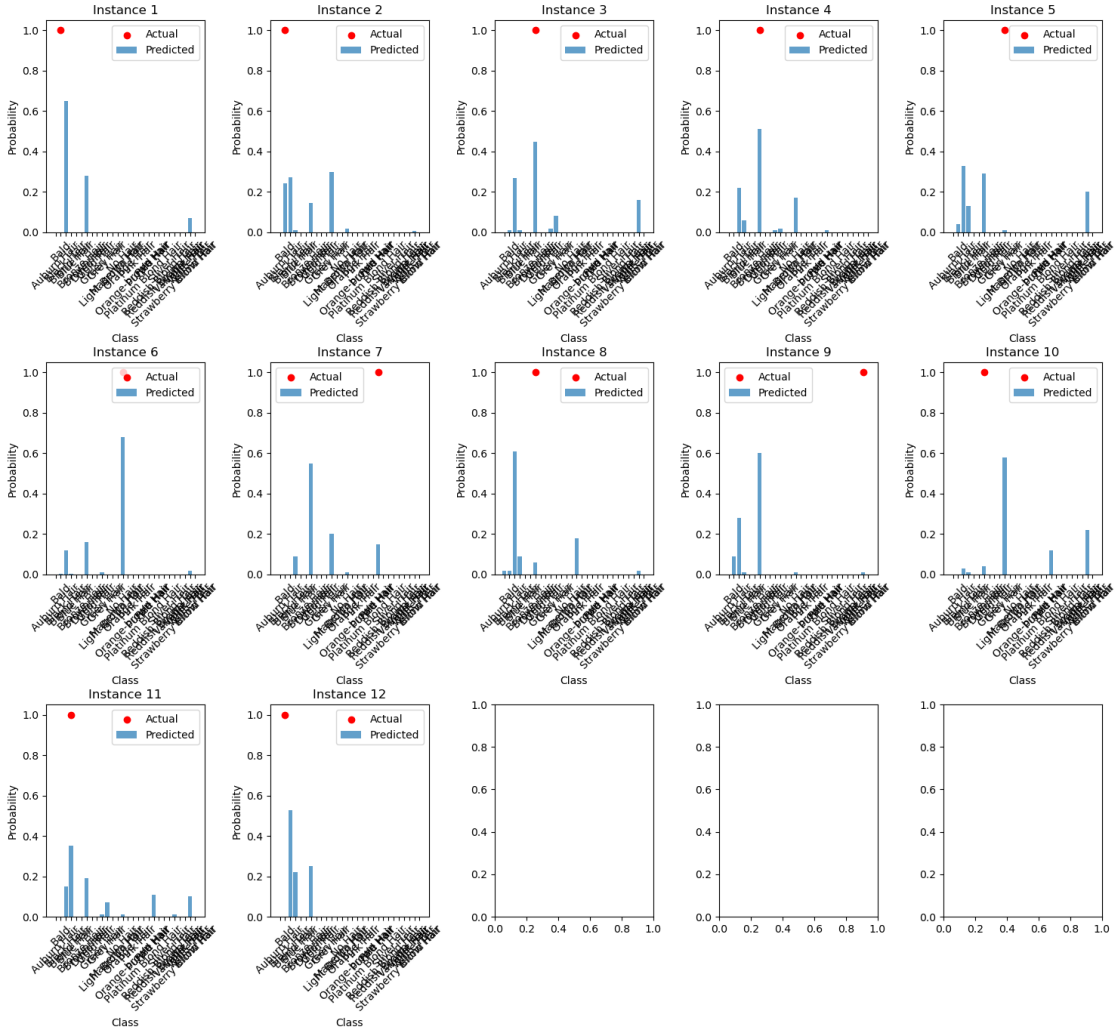
[ ]:
```
# Loop through each dataset
for rf_model, X_train, y_train, X_test, y_test, target_feature, class_names in␣
↪rf_models_combined:
    # Select a random subset of instances from the test data
    num_instances = min((int(len(X_test) * 0.1) if len(X_test) > 250 else␣
↪len(X_test)), 12)
    selected_indices = np.random.choice(len(X_test), num_instances,␣
↪replace=False)
    X_test_subset = X_test.iloc[selected_indices]
    y_test_subset = y_test[selected_indices]

    # Get the predicted probabilities for the selected instances in the test␣
↪data
```

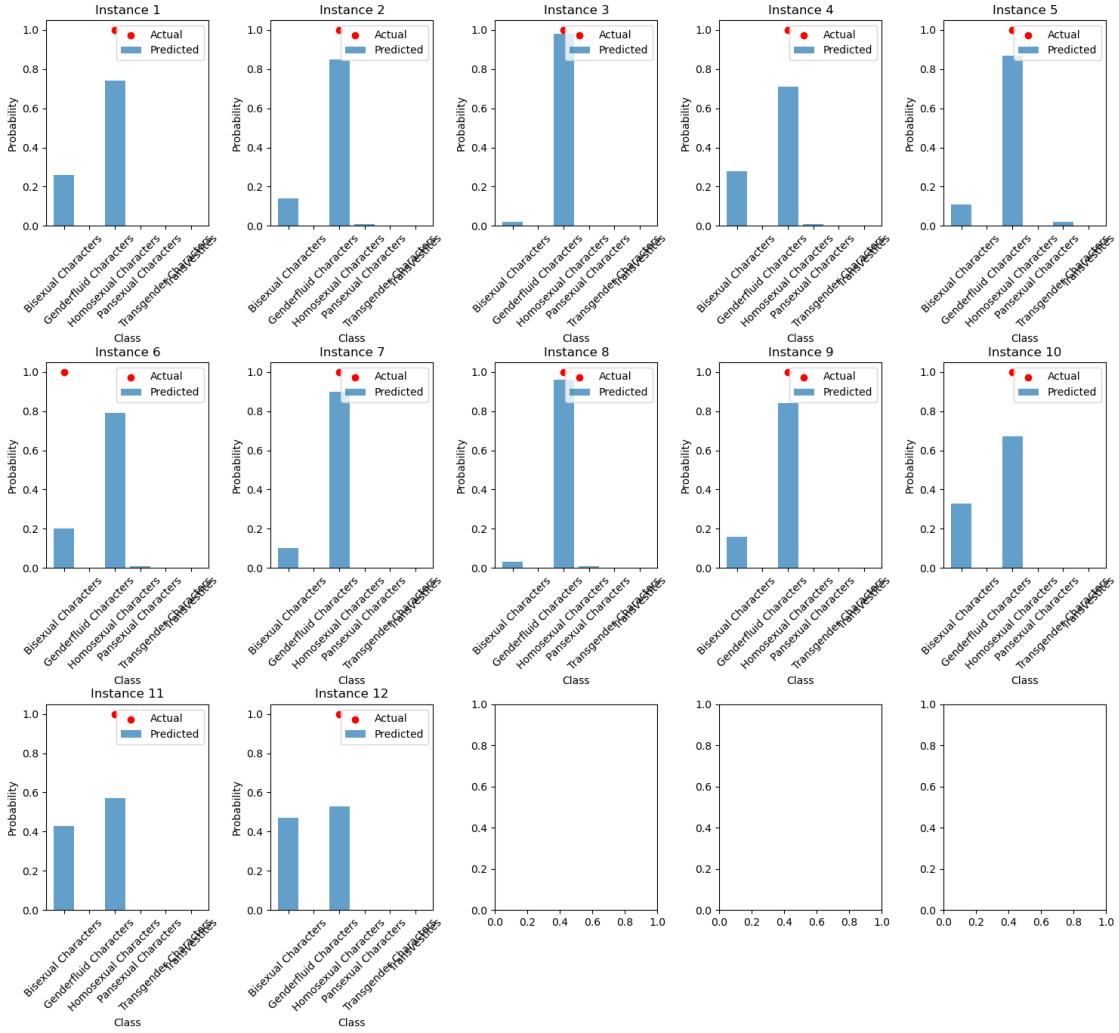
```
    predicted_probabilities = rf_model.predict_proba(X_test_subset)

    # Get the subset of class names corresponding to the number of classes
    subset_class_names = class_names[:predicted_probabilities.shape[1]]

    # Calculate the number of rows and columns for subplots
    num_instances_subset, num_classes = predicted_probabilities.shape
    num_columns = min(num_classes, 5)  # Limit the number of columns to avoid␣
↪too many subplots
    num_rows = math.ceil(num_instances_subset / num_columns)

    # Create a larger plot with subplots
    fig, axes = plt.subplots(num_rows, num_columns, figsize=(15, 15))
    fig.suptitle(f"Predicted Probabilities for {target_feature}", fontsize=16)

    # Loop through each instance and its corresponding predicted probabilities
    for i, (probs, ax) in enumerate(zip(predicted_probabilities, axes.
↪flatten())):
        actual_class = y_test_subset[i]  # Get the actual class value

        # Plot the predicted probabilities as a bar chart
        ax.bar(subset_class_names, probs, label="Predicted", alpha=0.7)

        # Plot the actual class value as a point on top of the predicted␣
↪probabilities
        ax.scatter(actual_class, 1, color="red", label="Actual")

        ax.set_title(f"Instance {i+1}")  # Set character name as the title
        ax.set_xlabel("Class")
        ax.set_ylabel("Probability")
        ax.set_xticks(range(len(subset_class_names)))  # Set tick positions
        ax.set_xticklabels(subset_class_names, rotation=45)  # Set tick labels
        ax.legend()  # Show legend

    # Adjust layout and display the plot
    plt.tight_layout()
    plt.subplots_adjust(top=0.9)
    plt.savefig(f"""figs/prob_charts/
↪Combined_{target_feature}_{selected_indices}_probabilities.png""")
    plt.show()
```

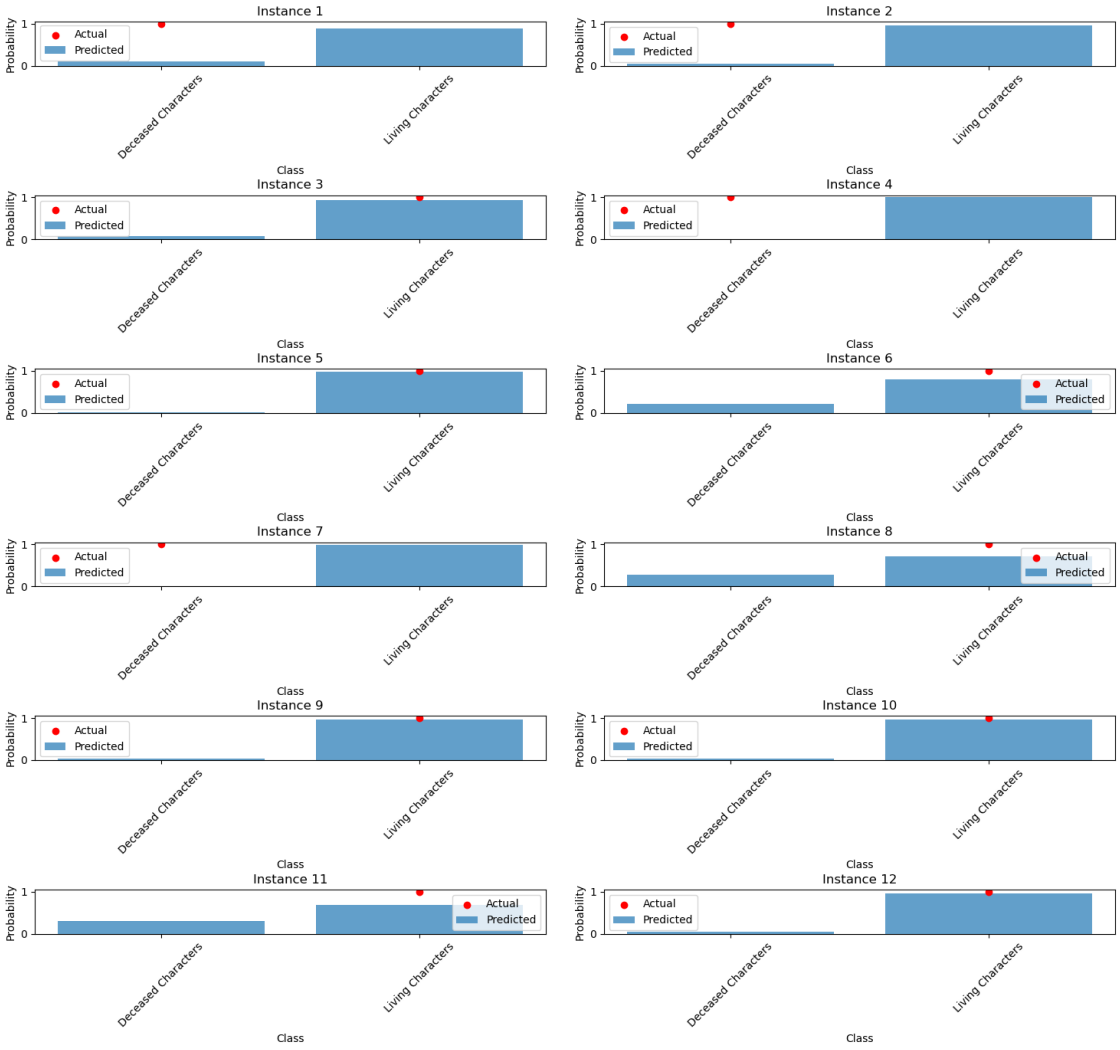

Predicted Probabilities for ALIGN
Instance 1
Instance 2
Instance 3
Instance 4
Instance 5
Instance 6
Instance 7
Instance 8
Instance 9
Instance 10
Instance 11
Instance 12
Actual
Predicted
Probability
Class
Bad Characters
Good Characters
Neutral Characters
Reformed Criminals

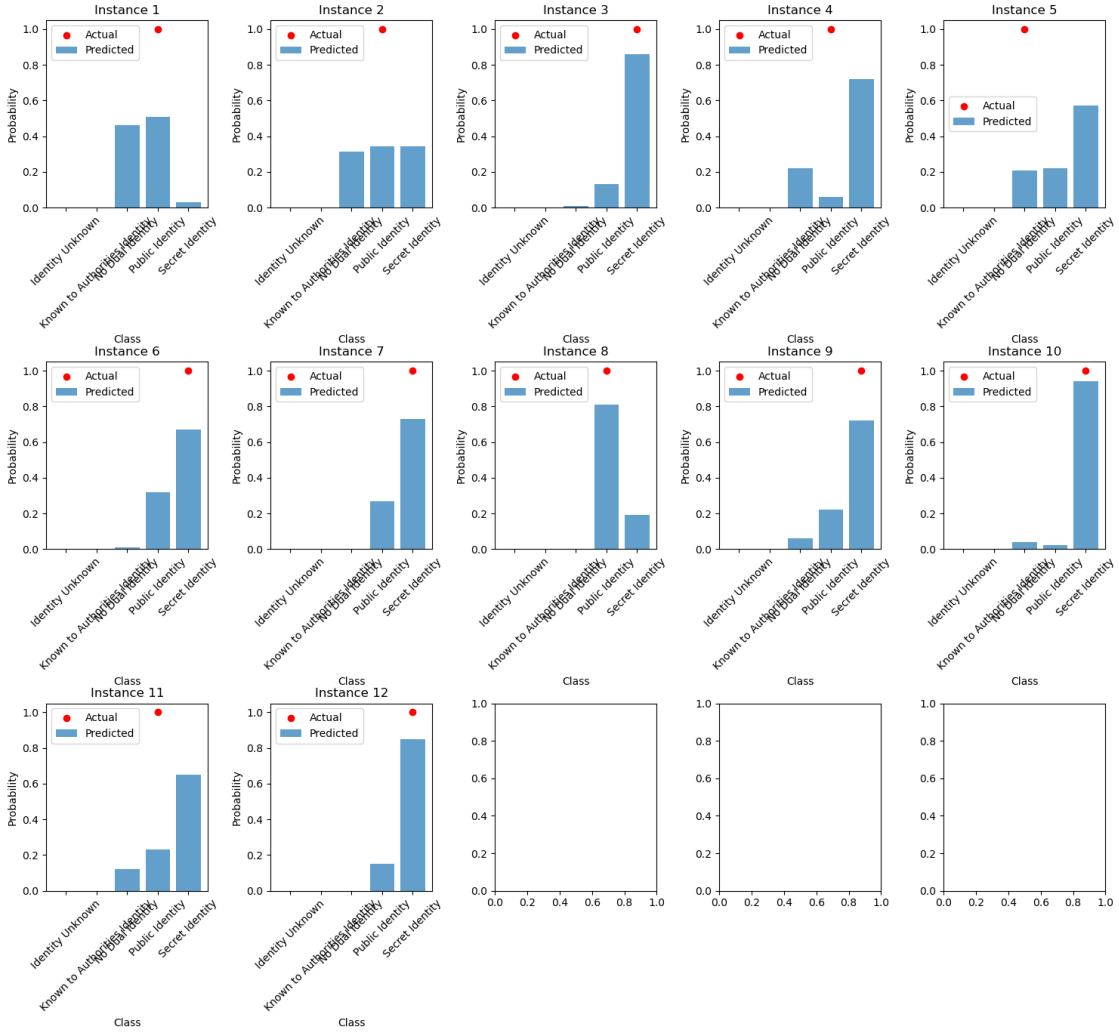

Predicted Probabilities for SEX
Instance 1
Instance 2
Instance 3
Instance 4
Instance 5
Instance 6
Instance 7
Instance 8
Instance 9
Instance 10
Instance 11
Instance 12
Actual
Predicted
Probability
Class
Agender Characters
Female Characters
Genderfluid Characters
Genderless Characters
Male Characters


Predicted Probabilities for EYE
Instance 1
Instance 2
Instance 3
Instance 4
Instance 5
Instance 6
Instance 7
Instance 8
Instance 9
Instance 10
Instance 11
Instance 12
Actual
Predicted
Probability
Class


Predicted Probabilities for HAIR
Instance 1
Instance 2
Instance 3
Instance 4
Instance 5
Instance 6
Instance 7
Instance 8
Instance 9
Instance 10
Instance 11
Instance 12
Actual
Predicted
Probability
Class


Predicted Probabilities for GSM
Instance 1
Instance 2
Instance 3
Instance 4
Instance 5
Instance 6
Instance 7
Instance 8
Instance 9
Instance 10
Instance 11
Instance 12
Actual
Predicted
Probability
Class
Bisexual Characters
Genderfluid Characters
Homosexual Characters
Pansexual Characters
Transgender Characters


Predicted Probabilities for ALIVE
Instance 1
Instance 2
Instance 3
Instance 4
Instance 5
Instance 6
Instance 7
Instance 8
Instance 9
Instance 10
Instance 11
Instance 12
Actual
Predicted
Probability
Class
Deceased Characters
Living Characters


Predicted Probabilities for ID
Instance 1
Instance 2
Instance 3
Instance 4
Instance 5
Instance 6
Instance 7
Instance 8
Instance 9
Instance 10
Instance 11
Instance 12
Actual
Predicted
Probability
Class
Identity Unknown
Known to Authorities Identity
Known to Author
No Data Identity
Public Identity
Secret Identity

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