MMA Fight Outcome Model

The purpose of this project is to create a binary classification model to predict the outcome of an MMA fight (win or loss for a given fighter) based on a set of features extracted from the database found at https://www.kaggle.com/datasets/danmcinerney/mma-differentials-and-elo?select=masterMLpublic.csv

The database consists of over 6000 unique fights and 513 feature columns for which data is collected on each fight. This project will explore two distinct models. The first will tackle the problem using a feed-forward neural network, whereas the second model will utilise an SVM classifier.

For more information on the problem statement and methodology, please read Summary.pdf or README.md

I. DATA PREPROCESSING

In [81]:

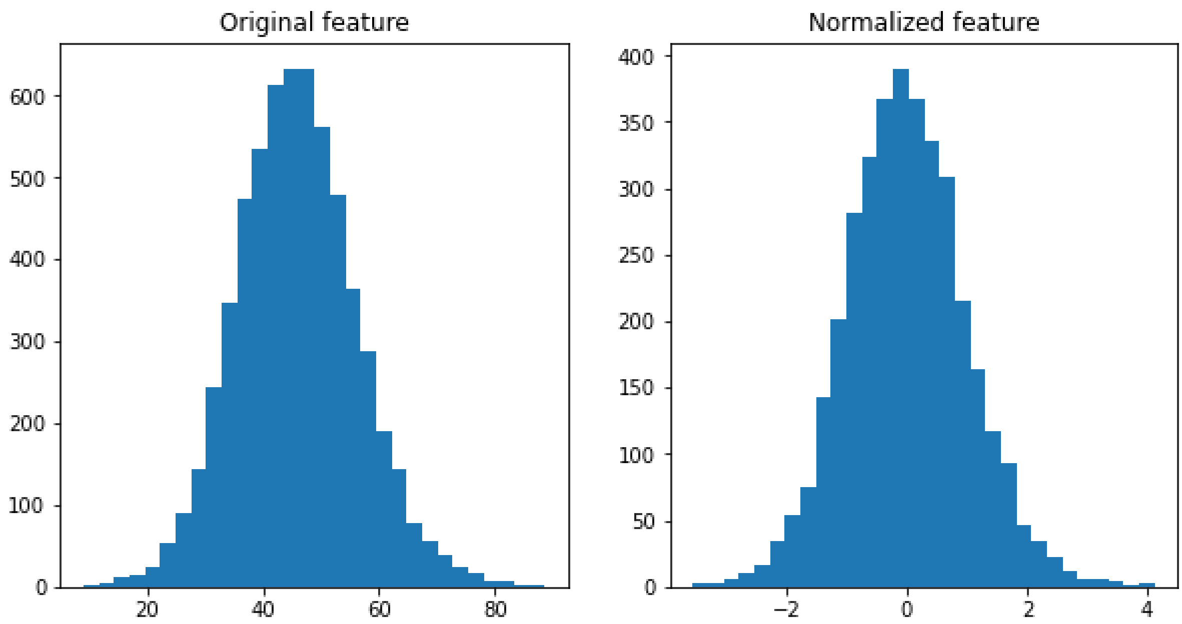
```
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler

# REMOVING ENTRIES WITH MISSING DATA

data = pd.read_csv('masterdataframe.csv')
data = data.dropna()
start_col = data.columns.get_loc("reach")
end_col = data.columns.get_loc("precomp_recent_avg_ground_strikes_attempts_pe
features = data.iloc[:, start_col:end_col]
target = data['result']

# SPLITTING DATA INTO TRAINING, VALIDATION, TESTING SETS

X_train, X_temp, y_train, y_temp = train_test_split(features, target, test_si
X_val, X_test, y_val, y_test = train_test_split(X_temp, y_temp, test_size=0.5

# NORMALISING

scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_val = scaler.transform(X_val)
X_test = scaler.transform(X_test)
```

Example visualisation of processed data for feature 200

In [83]:

```
import matplotlib.pyplot as plt

feature_idx = 200  # Choose the index of the feature you want to plot
original_feature = data.iloc[:, start_col + feature_idx]
normalized_feature = X_train[:, feature_idx]

plt.figure(figsize=(10, 5))
plt.subplot(1, 2, 1)
plt.hist(original_feature, bins=30)
plt.title('Original feature')
plt.subplot(1, 2, 2)
plt.hist(normalized_feature, bins=30)
```

```
plt.title('Normalized feature')
plt.show()
```



II. DEVELOPING MODEL 1: LOGISTIC REGRESSION AND A NEURAL NETWORK

Least Squares Approximation using LU Factorisation

In [84]:

```
import scipy.linalg as la

X_train = np.hstack([np.ones((X_train.shape[0], 1)), X_train])
X_val = np.hstack([np.ones((X_val.shape[0], 1)), X_val])
X_test = np.hstack([np.ones((X_test.shape[0], 1)), X_test])

alpha = 1e-3  # Regularization strength
XtX = X_train.T @ X_train + alpha * np.eye(X_train.shape[1])


# XtX = X_train.T @ X_train
Xty = X_train.T @ y_train

# LU Factorization
P, L, U = la.lu(XtX)

# Forward substitution
y_temp = la.solve(L, P @ Xty)

# Backward substitution
w = la.solve(U, y_temp)

def logistic_function(x):
    return 1 / (1 + np.exp(-x))

y_train_pred = logistic_function(X_train @ w)
y_val_pred = logistic_function(X_val @ w)
y_test_pred = logistic_function(X_test @ w)


threshold = 0.5
y_train_pred_label = (y_train_pred >= threshold).astype(int)
```

```
y_val_pred_label = (y_val_pred >= threshold).astype(int)
y_test_pred_label = (y_test_pred >= threshold).astype(int)
```

In [92]:

```
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_

accuracy_train = accuracy_score(y_train, y_train_pred_label)
precision_train = precision_score(y_train, y_train_pred_label)
recall_train = recall_score(y_train, y_train_pred_label)
f1_train = f1_score(y_train, y_train_pred_label)

accuracy_val = accuracy_score(y_val, y_val_pred_label)
precision_val = precision_score(y_val, y_val_pred_label)
recall_val = recall_score(y_val, y_val_pred_label)
f1_val = f1_score(y_val, y_val_pred_label)

accuracy_test = accuracy_score(y_test, y_test_pred_label)
precision_test = precision_score(y_test, y_test_pred_label)
recall_test = recall_score(y_test, y_test_pred_label)
f1_test = f1_score(y_test, y_test_pred_label)

print("Training set evaluation:")
print(f"Accuracy: {accuracy_train:.3f}")
print(f"Precision: {precision_train:.3f}")
print(f"Recall: {recall_train:.3f}")
print(f"F1 score: {f1_train:.3f}")

print("\nValidation set evaluation:")
print(f"Accuracy: {accuracy_val:.3f}")
print(f"Precision: {precision_val:.3f}")
print(f"Recall: {recall_val:.3f}")
print(f"F1 score: {f1_val:.3f}")

print("\nTest set evaluation:")
print(f"Accuracy: {accuracy_test:.3f}")
print(f"Precision: {precision_test:.3f}")
print(f"Recall: {recall_test:.3f}")
print(f"F1 score {f1_test:.3f}")
```

```
Training set evaluation:
Accuracy: 0.493
Precision: 0.490
Recall: 0.510
F1 score: 0.500

Validation set evaluation:
Accuracy: 0.510
Precision: 0.506
Recall: 0.500
F1 score: 0.503

Test set evaluation:
Accuracy: 0.517
Precision: 0.505
Recall: 0.541
F1 score 0.522
```

Refining the Logistic Regression: Elastic Net Regularisation

In [93]:

```
from sklearn.linear_model import SGDClassifier

# Prepare the data
X_train = np.hstack([np.ones((X_train.shape[0], 1)), X_train])
X_val = np.hstack([np.ones((X_val.shape[0], 1)), X_val])
X_test = np.hstack([np.ones((X_test.shape[0], 1)), X_test])
```

```
# Set regularization hyperparameters
alpha = 1e-3  # Regularization strength
l1_ratio = 0.5  # Ratio between L1 and L2 regularization

# Train the Elastic Net regularized logistic regression model
model = SGDClassifier(loss='log', penalty='elasticnet', alpha=alpha, l1_ratio
model.fit(X_train, y_train)

# Predict labels and probabilities
y_train_pred_label = model.predict(X_train)
y_train_pred = model.predict_proba(X_train)[:, 1]

y_val_pred_label = model.predict(X_val)
y_val_pred = model.predict_proba(X_val)[:, 1]

y_test_pred_label = model.predict(X_test)
y_test_pred = model.predict_proba(X_test)[:, 1]

# Evaluate the model
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_

accuracy_train = accuracy_score(y_train, y_train_pred_label)
precision_train = precision_score(y_train, y_train_pred_label)
recall_train = recall_score(y_train, y_train_pred_label)
f1_train = f1_score(y_train, y_train_pred_label)

accuracy_val = accuracy_score(y_val, y_val_pred_label)
precision_val = precision_score(y_val, y_val_pred_label)
recall_val = recall_score(y_val, y_val_pred_label)
f1_val = f1_score(y_val, y_val_pred_label)

accuracy_test = accuracy_score(y_test, y_test_pred_label)
precision_test = precision_score(y_test, y_test_pred_label)
recall_test = recall_score(y_test, y_test_pred_label)
f1_test = f1_score(y_test, y_test_pred_label)

print("Training set evaluation:")
print(f"Accuracy: {accuracy_train:.3f}")
print(f"Precision: {precision_train:.3f}")
print(f"Recall: {recall_train:.3f}")
print(f"F1 score: {f1_train:.3f}")

print("\nValidation set evaluation:")
print(f"Accuracy: {accuracy_val:.3f}")
print(f"Precision: {precision_val:.3f}")
print(f"Recall: {recall_val:.3f}")
print(f"F1 score: {f1_val:.3f}")

print("\nTest set evaluation:")
print(f"Accuracy: {accuracy_test:.3f}")
print(f"Precision: {precision_test:.3f}")
print(f"Recall: {recall_test:.3f}")
print(f"F1 score {f1_test:.3f}")
```

```
Training set evaluation:
Accuracy: 0.862
Precision: 0.851
Recall: 0.875
F1 score: 0.863

Validation set evaluation:
Accuracy: 0.821
Precision: 0.827
Recall: 0.807
F1 score: 0.817
```

```
Test set evaluation:
Accuracy: 0.811
Precision: 0.805
Recall: 0.808
F1 score 0.806
```

Introducing a Feed-foward Neural Network

In [100…

```
import tensorflow as tf
from tensorflow.keras import layers, models

def sigmoid(x):
    return 1 / (1 + np.exp(-x))

# Identify significant independent variables
significant_variables = np.where(np.abs(w[1:]) > 1e-2)[0]  # Adjust the thres
X_train_nn = X_train[:, 1:][:, significant_variables]
X_val_nn = X_val[:, 1:][:, significant_variables]
X_test_nn = X_test[:, 1:][:, significant_variables]

# Add logistic regression predictions as an input
X_train_nn = np.hstack([X_train_nn, y_train_pred.reshape(-1, 1)])
X_val_nn = np.hstack([X_val_nn, y_val_pred.reshape(-1, 1)])
X_test_nn = np.hstack([X_test_nn, y_test_pred.reshape(-1, 1)])

# Create a simple feedforward neural network
model = models.Sequential()
model.add(layers.Dense(1, activation='sigmoid', input_shape=(X_train_nn.shape

# Compile the model
model.compile(optimizer='adam', loss='binary_crossentropy', metrics=['accurac

# Train the model
history = model.fit(X_train_nn, y_train, epochs=50, batch_size=32, validation

# Evaluate the model on the test set
test_loss, test_accuracy = model.evaluate(X_test_nn, y_test)
print(f"Test loss: {test_loss}, Test accuracy: {test_accuracy}")
```

```
Epoch 1/50
114/114 [==============================] - 1s 2ms/step - loss: 0.5464 - accura
cy: 0.7202 - val_loss: 0.4795 - val_accuracy: 0.7646
Epoch 2/50
114/114 [==============================] - 0s 1ms/step - loss: 0.4330 - accura
cy: 0.7954 - val_loss: 0.4392 - val_accuracy: 0.8025
Epoch 3/50
114/114 [==============================] - 0s 1ms/step - loss: 0.4022 - accura
cy: 0.8146 - val_loss: 0.4235 - val_accuracy: 0.8082
Epoch 4/50
114/114 [==============================] - 0s 1ms/step - loss: 0.3871 - accura
cy: 0.8234 - val_loss: 0.4221 - val_accuracy: 0.8140
Epoch 5/50
114/114 [==============================] - 0s 1ms/step - loss: 0.3759 - accura
cy: 0.8297 - val_loss: 0.4085 - val_accuracy: 0.8181
Epoch 6/50
114/114 [==============================] - 0s 1ms/step - loss: 0.3677 - accura
cy: 0.8368 - val_loss: 0.4085 - val_accuracy: 0.8181
Epoch 7/50
114/114 [==============================] - 0s 1ms/step - loss: 0.3631 - accura
cy: 0.8398 - val_loss: 0.4049 - val_accuracy: 0.8214
Epoch 8/50
114/114 [==============================] - 0s 1ms/step - loss: 0.3569 - accura
cy: 0.8472 - val_loss: 0.4101 - val_accuracy: 0.8140
Epoch 9/50
114/114 [==============================] - 0s 1ms/step - loss: 0.3537 - accura
```

```
cy: 0.8415 - val_loss: 0.4030 - val_accuracy: 0.8181
Epoch 10/50
114/114 [==============================] - 0s 1ms/step - loss: 0.3506 - accura
cy: 0.8453 - val_loss: 0.4026 - val_accuracy: 0.8222
Epoch 11/50
114/114 [==============================] - 0s 1ms/step - loss: 0.3476 - accura
cy: 0.8478 - val_loss: 0.4119 - val_accuracy: 0.8206
Epoch 12/50
114/114 [==============================] - 0s 1ms/step - loss: 0.3446 - accura
cy: 0.8475 - val_loss: 0.4091 - val_accuracy: 0.8173
Epoch 13/50
114/114 [==============================] - 0s 1ms/step - loss: 0.3427 - accura
cy: 0.8519 - val_loss: 0.4072 - val_accuracy: 0.8263
Epoch 14/50
114/114 [==============================] - 0s 1ms/step - loss: 0.3414 - accura
cy: 0.8522 - val_loss: 0.4051 - val_accuracy: 0.8239
Epoch 15/50
114/114 [==============================] - 0s 1ms/step - loss: 0.3382 - accura
cy: 0.8538 - val_loss: 0.4023 - val_accuracy: 0.8247
Epoch 16/50
114/114 [==============================] - 0s 1ms/step - loss: 0.3371 - accura
cy: 0.8541 - val_loss: 0.4040 - val_accuracy: 0.8255
Epoch 17/50
114/114 [==============================] - 0s 1ms/step - loss: 0.3356 - accura
cy: 0.8522 - val_loss: 0.4067 - val_accuracy: 0.8230
Epoch 18/50
114/114 [==============================] - 0s 1ms/step - loss: 0.3354 - accura
cy: 0.8552 - val_loss: 0.4060 - val_accuracy: 0.8288
Epoch 19/50
114/114 [==============================] - 0s 1ms/step - loss: 0.3331 - accura
cy: 0.8552 - val_loss: 0.4065 - val_accuracy: 0.8313
Epoch 20/50
114/114 [==============================] - 0s 1ms/step - loss: 0.3316 - accura
cy: 0.8535 - val_loss: 0.4061 - val_accuracy: 0.8263
Epoch 21/50
114/114 [==============================] - 0s 1ms/step - loss: 0.3308 - accura
cy: 0.8546 - val_loss: 0.4090 - val_accuracy: 0.8263
Epoch 22/50
114/114 [==============================] - 0s 1ms/step - loss: 0.3291 - accura
cy: 0.8557 - val_loss: 0.4087 - val_accuracy: 0.8288
Epoch 23/50
114/114 [==============================] - 0s 1ms/step - loss: 0.3295 - accura
cy: 0.8601 - val_loss: 0.4060 - val_accuracy: 0.8313
Epoch 24/50
114/114 [==============================] - 0s 1ms/step - loss: 0.3265 - accura
cy: 0.8568 - val_loss: 0.4102 - val_accuracy: 0.8296
Epoch 25/50
114/114 [==============================] - 0s 1ms/step - loss: 0.3275 - accura
cy: 0.8623 - val_loss: 0.4093 - val_accuracy: 0.8280
Epoch 26/50
114/114 [==============================] - 0s 1ms/step - loss: 0.3261 - accura
cy: 0.8598 - val_loss: 0.4076 - val_accuracy: 0.8255
Epoch 27/50
114/114 [==============================] - 0s 1ms/step - loss: 0.3252 - accura
cy: 0.8607 - val_loss: 0.4071 - val_accuracy: 0.8263
Epoch 28/50
114/114 [==============================] - 0s 1ms/step - loss: 0.3240 - accura
cy: 0.8609 - val_loss: 0.4143 - val_accuracy: 0.8247
Epoch 29/50
114/114 [==============================] - 0s 1ms/step - loss: 0.3232 - accura
cy: 0.8612 - val_loss: 0.4143 - val_accuracy: 0.8280
Epoch 30/50
114/114 [==============================] - 0s 1ms/step - loss: 0.3227 - accura
cy: 0.8623 - val_loss: 0.4137 - val_accuracy: 0.8280
Epoch 31/50
114/114 [==============================] - 0s 1ms/step - loss: 0.3208 - accura
cy: 0.8618 - val_loss: 0.4100 - val_accuracy: 0.8346
Epoch 32/50
114/114 [==============================] - 0s 1ms/step - loss: 0.3206 - accura
```

```
cy: 0.8612 - val_loss: 0.4081 - val_accuracy: 0.8280
Epoch 33/50
114/114 [==============================] - 0s 1ms/step - loss: 0.3215 - accura
cy: 0.8620 - val_loss: 0.4113 - val_accuracy: 0.8321
Epoch 34/50
114/114 [==============================] - 0s 1ms/step - loss: 0.3200 - accura
cy: 0.8629 - val_loss: 0.4138 - val_accuracy: 0.8222
Epoch 35/50
114/114 [==============================] - 0s 1ms/step - loss: 0.3199 - accura
cy: 0.8623 - val_loss: 0.4126 - val_accuracy: 0.8305
Epoch 36/50
114/114 [==============================] - 0s 1ms/step - loss: 0.3193 - accura
cy: 0.8640 - val_loss: 0.4113 - val_accuracy: 0.8321
Epoch 37/50
114/114 [==============================] - 0s 1ms/step - loss: 0.3168 - accura
cy: 0.8637 - val_loss: 0.4178 - val_accuracy: 0.8230
Epoch 38/50
114/114 [==============================] - 0s 1ms/step - loss: 0.3179 - accura
cy: 0.8618 - val_loss: 0.4139 - val_accuracy: 0.8313
Epoch 39/50
114/114 [==============================] - 0s 1ms/step - loss: 0.3184 - accura
cy: 0.8604 - val_loss: 0.4135 - val_accuracy: 0.8296
Epoch 40/50
114/114 [==============================] - 0s 1ms/step - loss: 0.3164 - accura
cy: 0.8637 - val_loss: 0.4159 - val_accuracy: 0.8230
Epoch 41/50
114/114 [==============================] - 0s 1ms/step - loss: 0.3167 - accura
cy: 0.8615 - val_loss: 0.4153 - val_accuracy: 0.8239
Epoch 42/50
114/114 [==============================] - 0s 1ms/step - loss: 0.3155 - accura
cy: 0.8670 - val_loss: 0.4171 - val_accuracy: 0.8296
Epoch 43/50
114/114 [==============================] - 0s 1ms/step - loss: 0.3150 - accura
cy: 0.8615 - val_loss: 0.4156 - val_accuracy: 0.8255
Epoch 44/50
114/114 [==============================] - 0s 1ms/step - loss: 0.3156 - accura
cy: 0.8634 - val_loss: 0.4129 - val_accuracy: 0.8288
Epoch 45/50
114/114 [==============================] - 0s 1ms/step - loss: 0.3155 - accura
cy: 0.8598 - val_loss: 0.4198 - val_accuracy: 0.8214
Epoch 46/50
114/114 [==============================] - 0s 1ms/step - loss: 0.3146 - accura
cy: 0.8664 - val_loss: 0.4179 - val_accuracy: 0.8263
Epoch 47/50
114/114 [==============================] - 0s 1ms/step - loss: 0.3131 - accura
cy: 0.8648 - val_loss: 0.4180 - val_accuracy: 0.8255
Epoch 48/50
114/114 [==============================] - 0s 1ms/step - loss: 0.3131 - accura
cy: 0.8656 - val_loss: 0.4202 - val_accuracy: 0.8255
Epoch 49/50
114/114 [==============================] - 0s 1ms/step - loss: 0.3133 - accura
cy: 0.8675 - val_loss: 0.4169 - val_accuracy: 0.8255
Epoch 50/50
114/114 [==============================] - 0s 1ms/step - loss: 0.3129 - accura
cy: 0.8604 - val_loss: 0.4189 - val_accuracy: 0.8165
38/38 [==============================] - 0s 828us/step - loss: 0.4317 - accura
cy: 0.8166
Test loss: 0.4317360818386078, Test accuracy: 0.8166118264198303
```

Evaluation

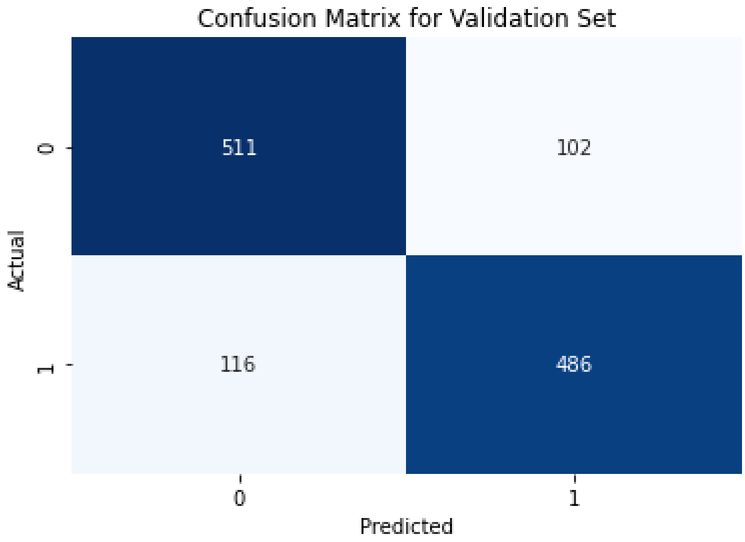
In [129…

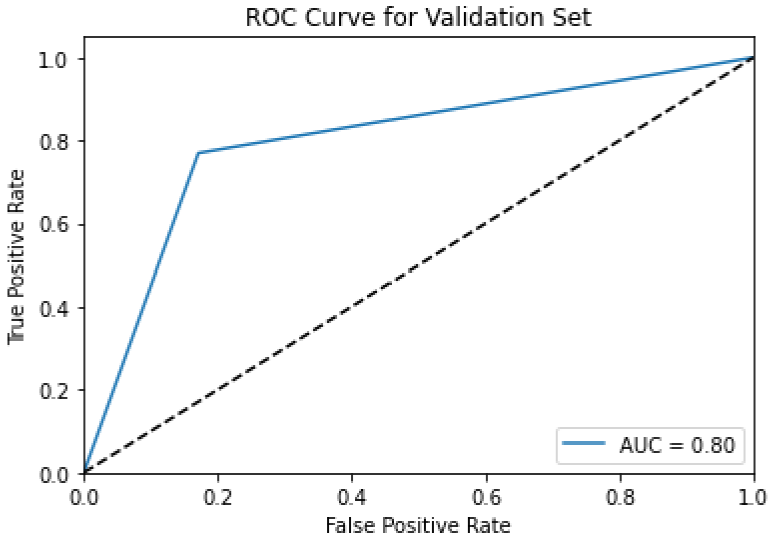
```python
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.metrics import confusion_matrix, roc_curve, roc_auc_score, preci

# Get the predictions from the hybrid model
y_train_pred_nn = model.predict(X_train_nn)
```

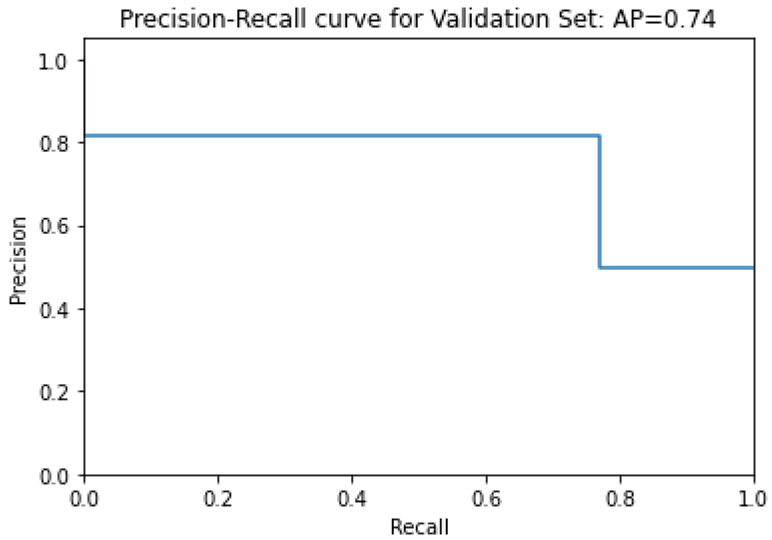
```
y_val_pred_nn = model.predict(X_val_nn)
y_test_pred_nn = model.predict(X_test_nn)

# Apply the threshold
threshold = 0.5
y_train_pred_label_nn = (y_train_pred_nn >= threshold).astype(int)
y_val_pred_label_nn = (y_val_pred_nn >= threshold).astype(int)
y_test_pred_label_nn = (y_test_pred_nn >= threshold).astype(int)

# Calculate the evaluation metrics
accuracy_train_nn = accuracy_score(y_train, y_train_pred_label_nn)
precision_train_nn = precision_score(y_train, y_train_pred_label_nn)
recall_train_nn = recall_score(y_train, y_train_pred_label_nn)
f1_train_nn = f1_score(y_train, y_train_pred_label_nn)

accuracy_val_nn = accuracy_score(y_val, y_val_pred_label_nn)
precision_val_nn = precision_score(y_val, y_val_pred_label_nn)
recall_val_nn = recall_score(y_val, y_val_pred_label_nn)
f1_val_nn = f1_score(y_val, y_val_pred_label_nn)

accuracy_test_nn = accuracy_score(y_test, y_test_pred_label_nn)
precision_test_nn = precision_score(y_test, y_test_pred_label_nn)
recall_test_nn = recall_score(y_test, y_test_pred_label_nn)
f1_test_nn = f1_score(y_test, y_test_pred_label_nn)

# Print the evaluation results
print("Training set evaluation:")
print(f"Accuracy: {accuracy_train_nn:.3f}")
print(f"Precision: {precision_train_nn:.3f}")
print(f"Recall: {recall_train_nn:.3f}")
print(f"F1 score: {f1_train_nn:.3f}")

print("\nValidation set evaluation:")
print(f"Accuracy: {accuracy_val_nn:.3f}")
print(f"Precision: {precision_val_nn:.3f}")
print(f"Recall: {recall_val_nn:.3f}")
print(f"F1 score: {f1_val_nn:.3f}")

print("\nTest set evaluation:")
print(f"Accuracy: {accuracy_test_nn:.3f}")
print(f"Precision: {precision_test_nn:.3f}")
print(f"Recall: {recall_test_nn:.3f}")
print(f"F1 score {f1_test_nn:.3f}")



cm = confusion_matrix(y_val, y_val_pred_label)
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', cbar=False)
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.title('Confusion Matrix for Validation Set')
plt.show()

y_val_proba = y_val_pred  # Use predicted probabilities from the logistic fun

fpr, tpr, _ = roc_curve(y_val, y_val_proba)
auc = roc_auc_score(y_val, y_val_proba)

plt.figure()
plt.plot(fpr, tpr, label=f'AUC = {auc:.2f}')
plt.plot([0, 1], [0, 1], 'k--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
```

```
plt.ylabel('True Positive Rate')
plt.title('ROC Curve for Validation Set')
plt.legend(loc='lower right')
plt.show()

precision, recall, _ = precision_recall_curve(y_val, y_val_proba)
average_precision = average_precision_score(y_val, y_val_proba)

plt.figure()
plt.step(recall, precision, where='post')
plt.xlabel('Recall')
plt.ylabel('Precision')
plt.ylim([0.0, 1.05])
plt.xlim([0.0, 1.0])
plt.title(f'Precision-Recall curve for Validation Set: AP={average_precision:
plt.show()
```

```
114/114 [==============================] - 0s 633us/step
38/38 [==============================] - 0s 640us/step
38/38 [==============================] - 0s 659us/step
Training set evaluation:
Accuracy: 0.871
Precision: 0.867
Recall: 0.875
F1 score: 0.871

Validation set evaluation:
Accuracy: 0.816
Precision: 0.828
Recall: 0.794
F1 score: 0.811

Test set evaluation:
Accuracy: 0.817
Precision: 0.821
Recall: 0.798
F1 score 0.809
```







III. DEVELOPING MODEL 2: SVM Classifier using QR Factorisation

Performing the QR Decomposition

In [ ]:

```
from scipy.stats import uniform, randint
from sklearn.svm import SVC
from sklearn.metrics import accuracy_score
from scipy.linalg import qr

# Perform QR factorization on the training data
Q_train, R_train = qr(X_train)

# Transform the validation data using the R matrix obtained from the training
X_val_transformed = np.dot(X_val, np.linalg.inv(R_train[:X_val.shape[1], :]))

# Transform the test data using the R matrix obtained from the training data
X_test_transformed = np.dot(X_test, np.linalg.inv(R_train[:X_test.shape[1], :
```

Refining the Parameters

In [121…

```
param_dist = {
    'C': uniform(loc=0, scale=4),
    'gamma': uniform(loc=0, scale=0.1),
    'kernel': ['linear', 'poly', 'rbf', 'sigmoid'],
    'degree': randint(2, 6),
```

```
    'coef0': uniform(loc=0, scale=1)
}

from sklearn.model_selection import RandomizedSearchCV

svm_classifier = SVC()

random_search = RandomizedSearchCV(
    svm_classifier,
    param_distributions=param_dist,
    n_iter=100,
    cv=5,
    verbose=2,
    n_jobs=-1,
    random_state=42
)

random_search.fit(X_val_transformed, y_val)

from sklearn.feature_selection import RFECV

svm_classifier_best = random_search.best_estimator_

rfe_cv = RFECV(svm_classifier_best, step=5, cv=5, scoring='accuracy', n_jobs=
rfe_cv.fit(X_val_transformed, y_val)


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

```
Fitting 5 folds for each of 100 candidates, totalling 500 fits
[Parallel(n_jobs=-1)]: Using backend LokyBackend with 16 concurrent workers.
[Parallel(n_jobs=-1)]: Done   9 tasks      | elapsed:    2.7s
[Parallel(n_jobs=-1)]: Done 130 tasks      | elapsed:   21.0s
[Parallel(n_jobs=-1)]: Done 333 tasks      | elapsed:   49.5s
[Parallel(n_jobs=-1)]: Done 500 out of 500 | elapsed:  1.2min finished
Fitting estimator with 515 features.
Fitting estimator with 510 features.
Fitting estimator with 505 features.
Fitting estimator with 500 features.
Fitting estimator with 495 features.
Fitting estimator with 490 features.
Fitting estimator with 485 features.
Fitting estimator with 480 features.
Fitting estimator with 475 features.
Fitting estimator with 470 features.
Fitting estimator with 465 features.
Fitting estimator with 460 features.
Fitting estimator with 455 features.
Fitting estimator with 450 features.
Fitting estimator with 445 features.
Fitting estimator with 440 features.
Fitting estimator with 435 features.
Fitting estimator with 430 features.
Fitting estimator with 425 features.
Fitting estimator with 420 features.
Fitting estimator with 415 features.
Fitting estimator with 410 features.
Fitting estimator with 405 features.
Fitting estimator with 400 features.
Fitting estimator with 395 features.
Fitting estimator with 390 features.
Fitting estimator with 385 features.
Fitting estimator with 380 features.
Fitting estimator with 375 features.
Fitting estimator with 370 features.
Fitting estimator with 365 features.
Fitting estimator with 360 features.
```

```
Fitting estimator with 355 features.
Fitting estimator with 350 features.
Fitting estimator with 345 features.
Fitting estimator with 340 features.
Fitting estimator with 335 features.
Fitting estimator with 330 features.
Fitting estimator with 325 features.
Fitting estimator with 320 features.
Fitting estimator with 315 features.
Fitting estimator with 310 features.
Fitting estimator with 305 features.
Fitting estimator with 300 features.
Fitting estimator with 295 features.
Fitting estimator with 290 features.
Fitting estimator with 285 features.
Fitting estimator with 280 features.
Fitting estimator with 275 features.
Fitting estimator with 270 features.
Fitting estimator with 265 features.
Fitting estimator with 260 features.
Fitting estimator with 255 features.
Fitting estimator with 250 features.
Fitting estimator with 245 features.
Fitting estimator with 240 features.
Fitting estimator with 235 features.
Fitting estimator with 230 features.
Fitting estimator with 225 features.
Fitting estimator with 220 features.
Fitting estimator with 215 features.
Fitting estimator with 210 features.
Fitting estimator with 205 features.
Fitting estimator with 200 features.
Fitting estimator with 195 features.
Fitting estimator with 190 features.
Fitting estimator with 185 features.
Fitting estimator with 180 features.
Fitting estimator with 175 features.
Fitting estimator with 170 features.
Fitting estimator with 165 features.
Fitting estimator with 160 features.
Fitting estimator with 155 features.
Fitting estimator with 150 features.
Fitting estimator with 145 features.
Fitting estimator with 140 features.
Fitting estimator with 135 features.
Fitting estimator with 130 features.
Fitting estimator with 125 features.
Fitting estimator with 120 features.
Fitting estimator with 115 features.
Fitting estimator with 110 features.
Fitting estimator with 105 features.
Fitting estimator with 100 features.
Fitting estimator with 95 features.
Fitting estimator with 90 features.
Fitting estimator with 85 features.
Fitting estimator with 80 features.
Fitting estimator with 75 features.
Fitting estimator with 70 features.
Fitting estimator with 65 features.
Fitting estimator with 60 features.
Fitting estimator with 55 features.
Fitting estimator with 50 features.
Fitting estimator with 45 features.
Fitting estimator with 40 features.
Fitting estimator with 35 features.
Optimal number of features : 30
```

In [123…

```
importances = rfe_cv.grid_scores_
indices = np.argsort(importances)[::-1]
```

```python
column_names = features.columns

print("Feature Ranking (Top 30):")

for i in range(30):
    index = indices[i]
    column_name = column_names[index]
    importance = importances[index]
    print(f"{i + 1}. {column_name} (Importance: {importance:.4f})")
```

```
Feature Ranking (Top 30):
1. control (Importance: 0.7868)
2. sub_attempts (Importance: 0.7844)
3. reversals (Importance: 0.7827)
4. takedowns_landed (Importance: 0.7770)
5. takedowns_attempts (Importance: 0.7704)
6. knockdowns (Importance: 0.7679)
7. sig_strikes_attempts (Importance: 0.7663)
8. sig_strikes_landed (Importance: 0.7621)
9. age (Importance: 0.7588)
10. total_strikes_landed (Importance: 0.7547)
11. leg_strikes_landed (Importance: 0.7481)
12. body_strikes_attempts (Importance: 0.7473)
13. head_strikes_attempts (Importance: 0.7473)
14. leg_strikes_attempts (Importance: 0.7449)
15. body_strikes_landed (Importance: 0.7449)
16. distance_strikes_attempts (Importance: 0.7416)
17. distance_strikes_landed (Importance: 0.7407)
18. total_strikes_attempts (Importance: 0.7399)
19. clinch_strikes_landed (Importance: 0.7399)
20. ground_strikes_landed (Importance: 0.7399)
21. clinch_strikes_attempts (Importance: 0.7358)
22. head_strikes_landed (Importance: 0.7350)
23. ground_strikes_attempts (Importance: 0.7342)
24. head_strikes_accuracy (Importance: 0.7317)
25. leg_strikes_accuracy (Importance: 0.7300)
26. body_strikes_accuracy (Importance: 0.7292)
27. sig_strikes_accuracy (Importance: 0.7276)
28. takedowns_accuracy (Importance: 0.7276)
29. clinch_strikes_accuracy (Importance: 0.7267)
30. total_strikes_def (Importance: 0.7259)
```

Training the SVM

In [117…

```python
best_features = selector.get_support(indices=True)
X_train_selected = X_train[:, best_features]
X_val_selected = X_val[:, best_features]

# Retrieve the best hyperparameters from the RandomizedSearchCV
best_params = random_search.best_params_

# Create an SVM classifier with the best hyperparameters
svm_clf = SVC(**best_params)

# Train the SVM classifier using the selected features
svm_clf.fit(X_train_selected, y_train)
```

Out[117…

```
SVC(C=3.630265895704372, coef0=0.24929222914887494, degree=2,
    gamma=0.05398410913016732, kernel='linear')
```

Evaluation

In [130…

```python
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.metrics import confusion_matrix, roc_curve, roc_auc_score, preci
```

```
def print_metrics(y_true, y_pred, label):
    accuracy = accuracy_score(y_true, y_pred)
    precision = precision_score(y_true, y_pred)
    recall = recall_score(y_true, y_pred)
    f1 = f1_score(y_true, y_pred)

    print(f"{label} - Accuracy: {accuracy:.4f}")
    print(f"{label} - Precision: {precision:.4f}")
    print(f"{label} - Recall: {recall:.4f}")
    print(f"{label} - F1 Score: {f1:.4f}")

y_train_pred = svm_clf.predict(X_train_selected)
print_metrics(y_train, y_train_pred, "Training")

y_val_pred = svm_clf.predict(X_val_selected)
print_metrics(y_val, y_val_pred, "Validation")

X_test_selected = X_test[:, best_features]
y_test_pred = svm_clf.predict(X_test_selected)
print_metrics(y_test, y_test_pred, "Test")

y_val_pred = svm_clf.predict(X_val_selected)

cm = confusion_matrix(y_val, y_val_pred)
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', cbar=False)
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.title('Confusion Matrix for Validation Set')
plt.show()

y_val_proba = svm_clf.decision_function(X_val_selected)

fpr, tpr, _ = roc_curve(y_val, y_val_proba)
auc = roc_auc_score(y_val, y_val_proba)

plt.figure()
plt.plot(fpr, tpr, label=f'AUC = {auc:.2f}')
plt.plot([0, 1], [0, 1], 'k--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curve for Validation Set')
plt.legend(loc='lower right')
plt.show()


precision, recall, _ = precision_recall_curve(y_val, y_val_proba)
average_precision = average_precision_score(y_val, y_val_proba)

plt.figure()
plt.step(recall, precision, where='post')
plt.xlabel('Recall')
plt.ylabel('Precision')
plt.ylim([0.0, 1.05])
plt.xlim([0.0, 1.0])
plt.title(f'Precision-Recall curve for Validation Set: AP={average_precision:
plt.show()
```

```
Training - Accuracy: 0.7916
Training - Precision: 0.8197
Training - Recall: 0.7436
Training - F1 Score: 0.7798
Validation - Accuracy: 0.7992
```

```
Validation - Precision: 0.8151
Validation - Recall: 0.7691
Validation - F1 Score: 0.7915
Test - Accuracy: 0.7969
Test - Precision: 0.8134
Test - Recall: 0.7572
Test - F1 Score: 0.7843
```