In [ ]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import joblib

import seaborn as sns
from sklearn.metrics import confusion_matrix

from sklearn.model_selection import TimeSeriesSplit
from sklearn.feature_selection import SequentialFeatureSelector
from sklearn.preprocessing import MinMaxScaler, StandardScaler

from sklearn.linear_model import RidgeClassifier
import xgboost as xgb
import lightgbm as lgb
from catboost import CatBoostClassifier
from sklearn.ensemble import RandomForestClassifier

from sklearn.metrics import accuracy_score, mean_squared_error

from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import LSTM, Dense, Dropout
from tensorflow.keras.optimizers import Adam
```

In [ ]:
```
TRAINING = True
```

In [ ]:
```
def plot_confusion_matrix(y_test, y_pred, class_names=None, figsize=(8, 6

    # Generate the confusion matrix
    cm = confusion_matrix(y_test, y_pred)

    # If class names are not provided, generate generic labels
    if class_names is None:
        class_names = [f"Class {i}" for i in range(cm.shape[0])]

    # Create a heatmap
    plt.figure(figsize=figsize)
    sns.heatmap(cm, annot=True, fmt="d", cmap="Blues", xticklabels=class_

    # Labels and title
    plt.xlabel("Predicted Label")
    plt.ylabel("True Label")
    plt.title("Confusion Matrix")
    plt.show()
```

In [ ]:
```
def save_model(model, model_name:str):
    file_name = f'{model_name}.model'
    joblib.dump(model,file_name)

def load_model(model_name):
    return joblib.load(f'{model_name}.model')

def print_accuracy(y_pred, y_test, model_name:str = None):
    if model_name:
        print(f"This is the result for {model_name}:")
    print(f"The accuracy score is: {accuracy_score(y_pred, y_test)}")
    print(f"THe MSE is: {mean_squared_error(y_pred, y_test)}")
    plot_confusion_matrix(y_test, y_pred, class_names=['Loss', 'Win'])
    print("----------------------------------------------------")
    return
```

In [ ]:
```
'''
def get_model(model_code):
    model_list =
    {
        "rf" : "random forest"
        "xgb" : "xgboost"
        "cbt" : "catboost"
        "lgb": "lightgbm"
    }
'''
```

Out[ ]:
```
'\ndef get_model(model_code):\n    model_list =\n    {\n        "rf" : "r
andom forest"\n        "xgb" : "xgboost"\n        "cbt" : "catboost"\n
"lgb": "lightgbm"\n    }\n'
```

Data import and cleaning

In [ ]:
```
df = pd.read_csv("nba_games2.csv", index_col =0)
```

In [ ]:
```
df.describe()
```

Out[ ]:

	mp	mp.1	fg	fga	fg%	3
count	8898.000000	8898.000000	8898.000000	8898.000000	8898.000000	8898.00000
mean	241.550910	241.550910	41.122275	88.137671	0.467570	12.47145
std	6.756057	6.756057	5.193318	7.034097	0.055022	3.90414
min	240.000000	240.000000	23.000000	64.000000	0.277000	2.00000
25%	240.000000	240.000000	38.000000	83.000000	0.430000	10.00000
50%	240.000000	240.000000	41.000000	88.000000	0.467000	12.00000
75%	240.000000	240.000000	45.000000	93.000000	0.506000	15.00000
max	315.000000	315.000000	65.000000	121.000000	0.687000	29.00000

8 rows × 150 columns

In [ ]:
```
df.head()
```

Out[ ]:

	mp	mp.1	fg	fga	fg%	3p	3pa	3p%	ft	fta	...	tov%_max_opp	usg
0	240.0	240.0	42.0	86.0	0.488	6.0	23.0	0.261	17.0	23.0	...	20.5	
1	240.0	240.0	43.0	90.0	0.478	7.0	28.0	0.250	24.0	34.0	...	100.0	
2	240.0	240.0	34.0	91.0	0.374	15.0	46.0	0.326	21.0	28.0	...	33.8	
3	240.0	240.0	40.0	94.0	0.426	9.0	36.0	0.250	17.0	26.0	...	17.0	
4	240.0	240.0	37.0	94.0	0.394	10.0	32.0	0.313	9.0	15.0	...	19.4	

5 rows × 154 columns

In [ ]:
```
# Sort data and drop meaningless columns
df = df.sort_values("date")
df = df.reset_index(drop=True)
df = df.drop(["mp.1", "mp_max.1","mp_opp.1", "mp_max_opp.1","index_opp"],
```

In [ ]:
```
# Add target data for model training
def add_target(team):
    team["target"] = team["won"].shift(-1)
    return team

df = df.groupby("team", group_keys=False).apply(add_target)
df["target"][pd.isnull(df["target"])] = 2
df["target"] = df["target"].astype(int, errors ="ignore")
```

```
/var/folders/fq/_3b4tsjj5sv_d2gh65lk7ps40000gn/T/ipykernel_29827/21412350
60.py:7: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-do
cs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  df["target"][pd.isnull(df["target"])] = 2
```

In [ ]:

```
# Get rid of data with NA values
nulls = pd.isnull(df)
nulls = nulls.sum()
nulls = nulls[nulls>0]

valid_columns = df.columns[~df.columns.isin(nulls.index)]
df = df[valid_columns].copy()
```

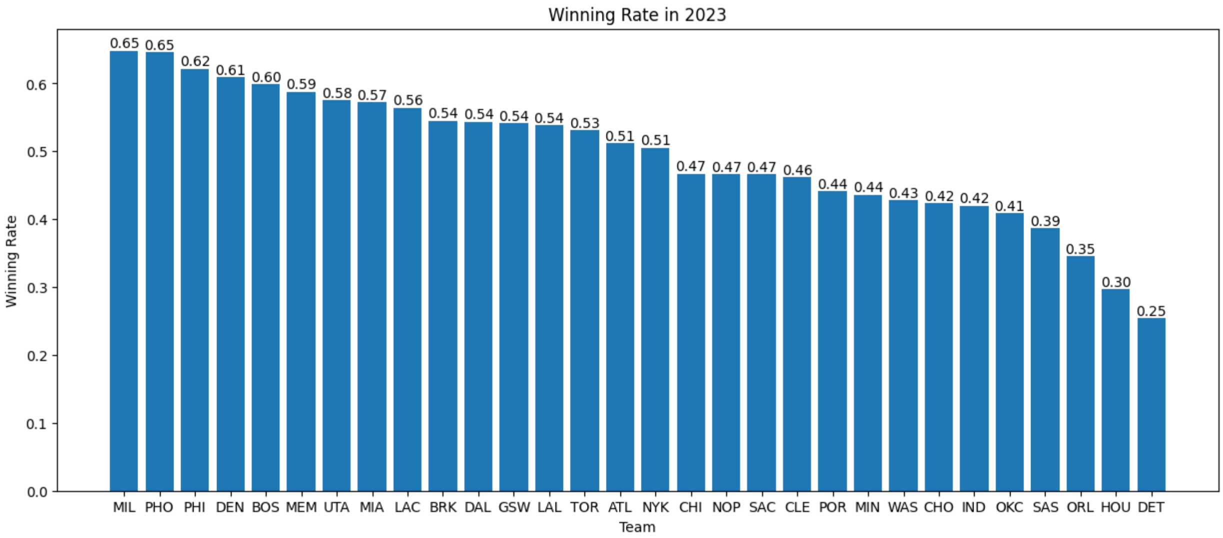
Winning Rate

In [ ]:

```
def add_value_in_bar(ax, bars):
    # Add the winning rate inside each bar
    for bar in bars:
        yval = bar.get_height()
        ax.text(
            bar.get_x() + bar.get_width() / 2,  # X position
            yval,  # Y position
            f"{yval:.2f}",  # Text to display (formatted to 2 decimal pla
            ha="center",  # Center alignment
            va="bottom"  # Position text at the bottom of the value
        )
```

In [ ]:

```
df_2023 = df[df["season"] == 2023]
df_team = df[["won", "team"]].groupby(["team"]).mean()
df_team = df_team.sort_values('won', ascending=False)

fig, ax = plt.subplots(figsize=(15, 6))

bars = ax.bar(df_team.index,df_team["won"])
add_value_in_bar(ax, bars)

ax.set_title("Winning Rate in 2023")
ax.set_xlabel("Team")
ax.set_ylabel("Winning Rate")

plt.show()
```



Winning Rate based on home or guest team

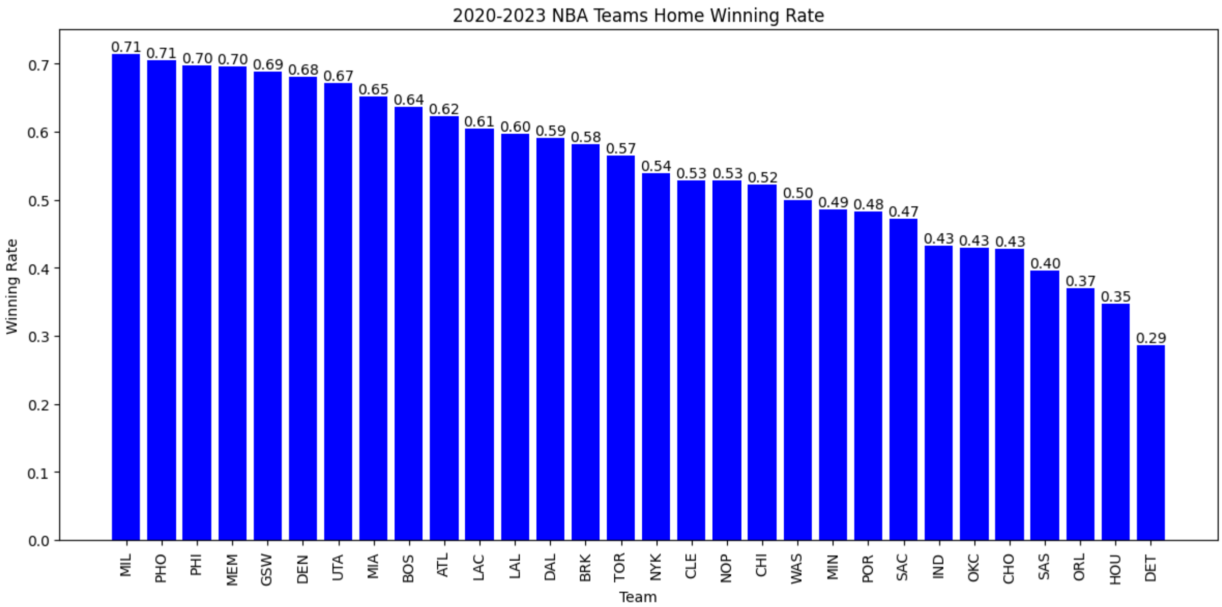
In [ ]:
```
df_team = df[["won","team","home"]].groupby(["team","home"]).mean()
df_team.head(6)
```

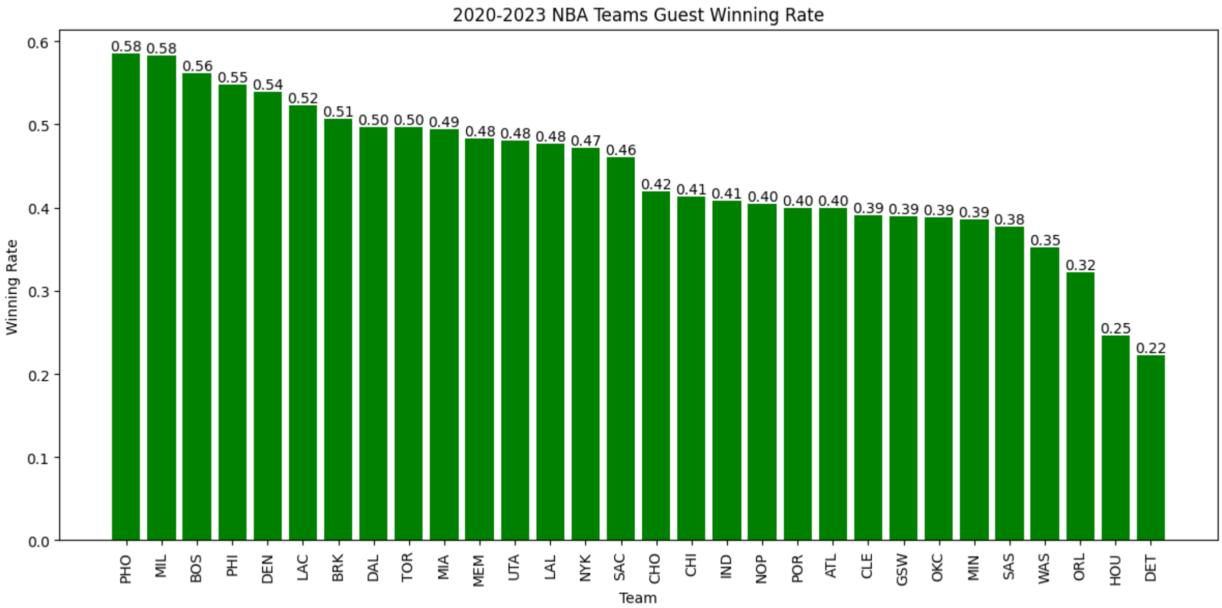
Out[ ]:

		won
team	**home**	
ATL	**0**	0.400000
	1	0.622517
BOS	**0**	0.561404
	1	0.635838
BRK	**0**	0.506757
	1	0.581699

In [ ]:
```
# Assuming df_team is your dataframe after groupby
df_team = df[["won", "team", "home"]].groupby(["team", "home"]).mean()

# Unstack the 'home' column so we have separate columns for home and away
df_team_unstacked = df_team.unstack()

# Rename the columns for clarity
df_team_unstacked.columns = ['guest', 'home']

# Sorting by home and guest win rates separately
home_sorted = df_team_unstacked.sort_values('home', ascending=False)
guest_sorted = df_team_unstacked.sort_values('guest', ascending=False)

# Create subplots: 2 rows, 1 column
fig, (ax1, ax2) = plt.subplots(2, 1, figsize=(12, 12))

# Plotting the home winning rate on the left (ax1)
bars = ax1.bar(home_sorted.index, home_sorted['home'], color='blue', labe
add_value_in_bar(ax1, bars)

ax1.set_xlabel('Team')
ax1.set_ylabel('Winning Rate')
ax1.set_title('2020-2023 NBA Teams Home Winning Rate')
ax1.set_xticklabels(home_sorted.index, rotation=90)

# Plotting the guest winning rate on the right (ax2)
bars = ax2.bar(guest_sorted.index, guest_sorted['guest'], color='green', 
add_value_in_bar(ax2, bars)

ax2.set_xlabel('Team')
ax2.set_ylabel('Winning Rate')
ax2.set_title('2020-2023 NBA Teams Guest Winning Rate')
ax2.set_xticklabels(guest_sorted.index, rotation=90)


# Adjust layout for better spacing
plt.tight_layout()
plt.show()
```

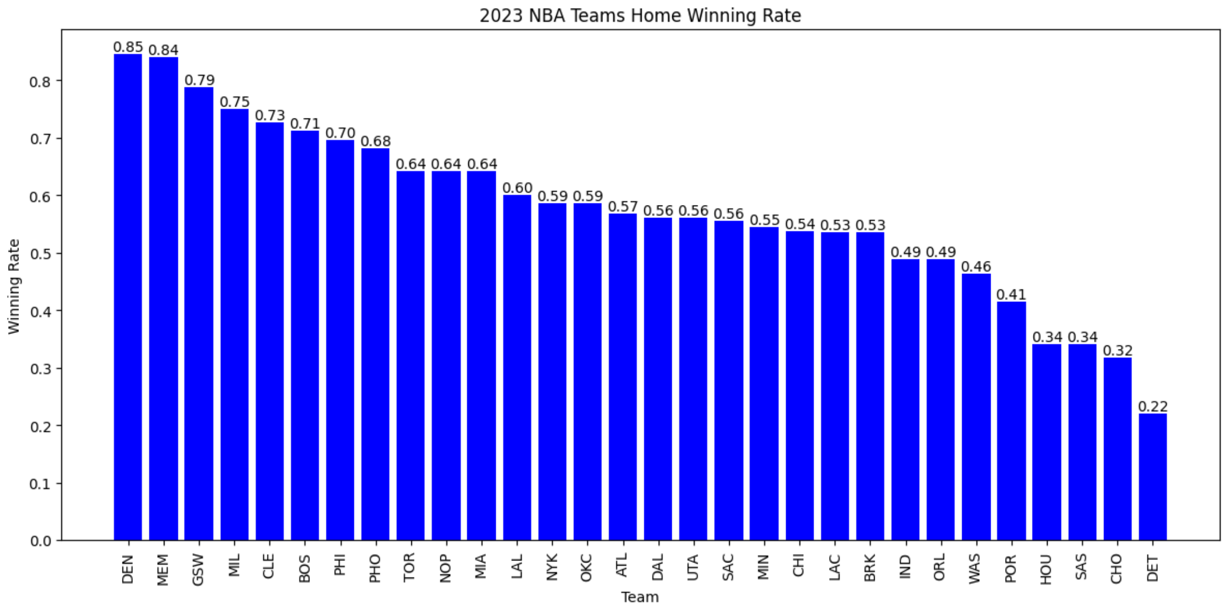
```
/var/folders/fq/_3b4tsjj5sv_d2gh65lk7ps40000gn/T/ipykernel_29827/29236674
46.py:24: UserWarning: set_ticklabels() should only be used with a fixed
number of ticks, i.e. after set_ticks() or using a FixedLocator.
  ax1.set_xticklabels(home_sorted.index, rotation=90)
/var/folders/fq/_3b4tsjj5sv_d2gh65lk7ps40000gn/T/ipykernel_29827/29236674
46.py:33: UserWarning: set_ticklabels() should only be used with a fixed
number of ticks, i.e. after set_ticks() or using a FixedLocator.
  ax2.set_xticklabels(guest_sorted.index, rotation=90)
```

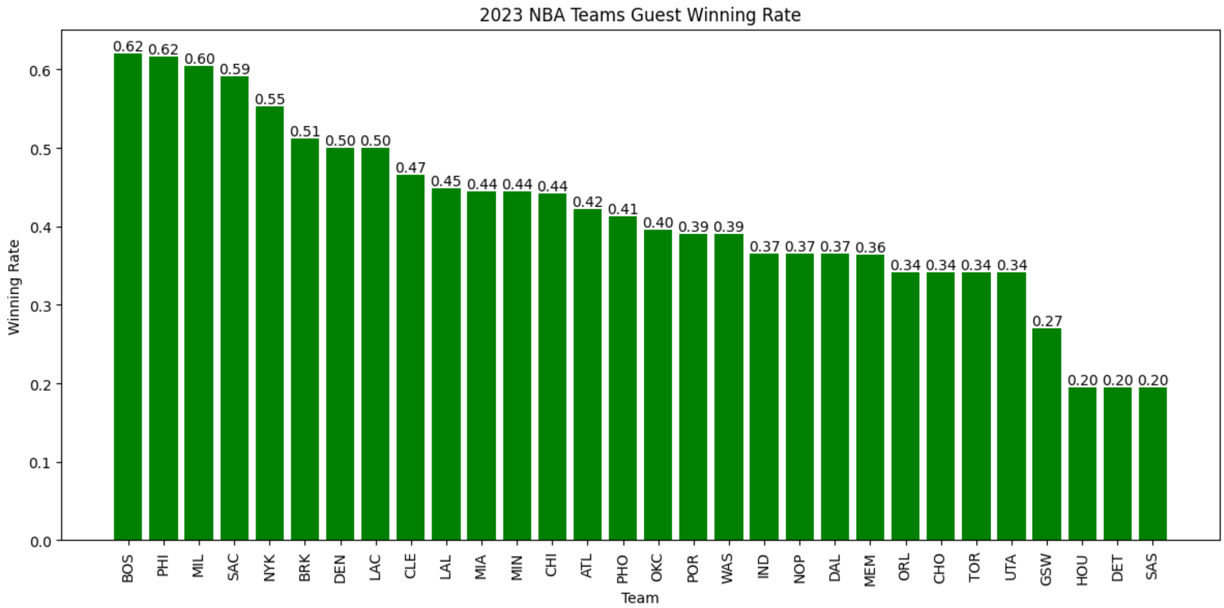

2020-2023 NBA Teams Home Winning Rate
Winning Rate
Team
MIL PHO PHI MEM GSW DEN UTA MIA BOS ATL LAC LAL DAL BRK TOR NYK CLE NOP CHI WAS MIN POR SAC IND OKC CHO SAS ORL HOU DET
0.71 0.71 0.70 0.70 0.69 0.68 0.67 0.65 0.64 0.62 0.61 0.60 0.59 0.58 0.57 0.54 0.53 0.53 0.52 0.50 0.49 0.48 0.47 0.43 0.43 0.43 0.40 0.37 0.35 0.29


2020-2023 NBA Teams Guest Winning Rate
Winning Rate
Team
PHO MIL BOS PHI DEN LAC BRK DAL TOR MIA MEM UTA LAL NYK SAC CHO CHI IND NOP POR ATL CLE GSW OKC MIN SAS WAS ORL HOU DET
0.58 0.58 0.56 0.55 0.54 0.52 0.51 0.50 0.50 0.49 0.48 0.48 0.48 0.47 0.46 0.42 0.41 0.41 0.40 0.40 0.40 0.39 0.39 0.39 0.39 0.38 0.35 0.32 0.25 0.22

In [ ]:
```
# Assuming df_team is your dataframe after groupby
df_team = df_2023[["won", "team", "home"]].groupby(["team", "home"]).mean

# Unstack the 'home' column so we have separate columns for home and away
df_team_unstacked = df_team.unstack()

# Rename the columns for clarity
df_team_unstacked.columns = ['guest', 'home']

# Sorting by home and guest win rates separately
home_sorted = df_team_unstacked.sort_values('home', ascending=False)
guest_sorted = df_team_unstacked.sort_values('guest', ascending=False)

# Create subplots: 2 rows, 1 column
fig, (ax1, ax2) = plt.subplots(2, 1, figsize=(12, 12))

# Plotting the home winning rate on the left (ax1)
bars = ax1.bar(home_sorted.index, home_sorted['home'], color='blue', labe
add_value_in_bar(ax1, bars)

ax1.set_xlabel('Team')
ax1.set_ylabel('Winning Rate')
ax1.set_title('2023 NBA Teams Home Winning Rate')
ax1.set_xticklabels(home_sorted.index, rotation=90)

# Plotting the guest winning rate on the right (ax2)
bars = ax2.bar(guest_sorted.index, guest_sorted['guest'], color='green',
add_value_in_bar(ax2, bars)

ax2.set_xlabel('Team')
ax2.set_ylabel('Winning Rate')
ax2.set_title('2023 NBA Teams Guest Winning Rate')
ax2.set_xticklabels(guest_sorted.index, rotation=90)

# Adjust layout for better spacing
plt.tight_layout()
plt.show()
```

```
/var/folders/fq/_3b4tsjj5sv_d2gh65lk7ps40000gn/T/ipykernel_29827/8374502
2.py:24: UserWarning: set_ticklabels() should only be used with a fixed n
umber of ticks, i.e. after set_ticks() or using a FixedLocator.
  ax1.set_xticklabels(home_sorted.index, rotation=90)
/var/folders/fq/_3b4tsjj5sv_d2gh65lk7ps40000gn/T/ipykernel_29827/8374502
2.py:33: UserWarning: set_ticklabels() should only be used with a fixed n
umber of ticks, i.e. after set_ticks() or using a FixedLocator.
  ax2.set_xticklabels(guest_sorted.index, rotation=90)
```





Scaling

In [ ]:
```
# Remove columns that are not going to be scaled
removed_columns_df = ["season", "date","won","target","team","team_opp"]

# Get the columns we want to scale on
selected_columns_df = df.columns[~df.columns.isin(removed_columns_df)]

# Rescale the data
scaler = MinMaxScaler()
df[selected_columns_df] = scaler.fit_transform(df[selected_columns_df])
```

Rolling

In [ ]:
```
df_rolling = df[list(selected_columns_df) + ["won", "team", "season"]]

def find_team_averages(team):
    numeric_columns = team.select_dtypes(include=[np.number])
    rolling = numeric_columns.rolling(10).mean()
    # Reattach the non-numeric columns (team, season)
    rolling[["team", "season"]] = team[["team", "season"]]
    return rolling

df_rolling = df_rolling.groupby(["team", "season"], group_keys=False).app
```

In [ ]:
```
rolling_cols = [f"{col}_10" for col in df_rolling.columns]
df_rolling.columns = rolling_cols
df_rolling = pd.concat([df, df_rolling], axis=1)
df_rolling = df_rolling.dropna()
```

In [ ]:
```
df_rolling
```

Out[ ]:

	mp	fg	fga	fg%	3p	3pa	3p%	ft	ft
244	0.0	0.357143	0.526316	0.309756	0.444444	0.754717	0.334432	0.487805	0.5
248	0.0	0.380952	0.473684	0.370732	0.370370	0.415094	0.490939	0.341463	0.3
250	0.0	0.476190	0.333333	0.587805	0.185185	0.226415	0.397035	0.585366	0.6
253	0.0	0.285714	0.421053	0.295122	0.148148	0.283019	0.268534	0.219512	0.3
255	0.0	0.452381	0.561404	0.392683	0.481481	0.603774	0.461285	0.439024	0.4
...	...	...	...	...	...	...	...	...	..
8893	0.0	0.261905	0.491228	0.226829	0.333333	0.471698	0.390445	0.317073	0.3
8894	0.0	0.380952	0.263158	0.529268	0.444444	0.339623	0.696870	0.341463	0.3
8895	0.0	0.285714	0.245614	0.419512	0.222222	0.283019	0.400329	0.365854	0.3
8896	0.0	0.238095	0.561404	0.163415	0.259259	0.471698	0.296540	0.292683	0.2
8897	0.0	0.357143	0.350877	0.426829	0.111111	0.339623	0.168040	0.268293	0.4

7818 rows × 280 columns

In [ ]:
```
def shift_col(team, col_name):
    next_col = team[col_name].shift(-1)
    return next_col

def add_col(df, col_name):
    return df.groupby("team", group_keys=False).apply(lambda x: shift_col

df_rolling["home_next"] = add_col(df_rolling, "home")
df_rolling["team_opp_next"] = add_col(df_rolling, "team_opp")
df_rolling["date_next"] = add_col(df_rolling, "date")
```

In [ ]:
```
df_rolling
```

Out[ ]:

	mp	fg	fga	fg%	3p	3pa	3p%	ft	fta
244	0.0	0.357143	0.526316	0.309756	0.444444	0.754717	0.334432	0.487805	0.50
248	0.0	0.380952	0.473684	0.370732	0.370370	0.415094	0.490939	0.341463	0.38
250	0.0	0.476190	0.333333	0.587805	0.185185	0.226415	0.397035	0.585366	0.68
253	0.0	0.285714	0.421053	0.295122	0.148148	0.283019	0.268534	0.219512	0.32
255	0.0	0.452381	0.561404	0.392683	0.481481	0.603774	0.461285	0.439024	0.40
...	...	...	...	...	...	...	...	...	..
8893	0.0	0.261905	0.491228	0.226829	0.333333	0.471698	0.390445	0.317073	0.34
8894	0.0	0.380952	0.263158	0.529268	0.444444	0.339623	0.696870	0.341463	0.38
8895	0.0	0.285714	0.245614	0.419512	0.222222	0.283019	0.400329	0.365854	0.36
8896	0.0	0.238095	0.561404	0.163415	0.259259	0.471698	0.296540	0.292683	0.28
8897	0.0	0.357143	0.350877	0.426829	0.111111	0.339623	0.168040	0.268293	0.42

7818 rows × 283 columns

In [ ]:
```
full = df_rolling.merge(df_rolling[rolling_cols + ["team_opp_next", "date
                left_on=["team", "date_next"],
                right_on=["team_opp_next", "date_next"])
```

In [ ]:
```
full[["team_x", "team_opp_next_x", "team_y", "team_opp_next_y", "date_nex
```

Out[ ]:

	team_x	team_opp_next_x	team_y	team_opp_next_y	date_next
0	NYK	CLE	CLE	NYK	2020-01-20
1	CLE	NYK	NYK	CLE	2020-01-20
2	MIA	WAS	WAS	MIA	2020-01-22
3	WAS	MIA	MIA	WAS	2020-01-22
4	UTA	GSW	GSW	UTA	2020-01-22
...	...	...	...	...	...
7735	DEN	MIA	MIA	DEN	2023-06-07
7736	DEN	MIA	MIA	DEN	2023-06-09
7737	MIA	DEN	DEN	MIA	2023-06-09
7738	DEN	MIA	MIA	DEN	2023-06-12
7739	MIA	DEN	DEN	MIA	2023-06-12

7740 rows × 5 columns

In [ ]:

```
removed_columns_full = list(full.columns[full.dtypes == "object"]) + remo
selected_columns_full = full.columns[~full.columns.isin(removed_columns_f
```

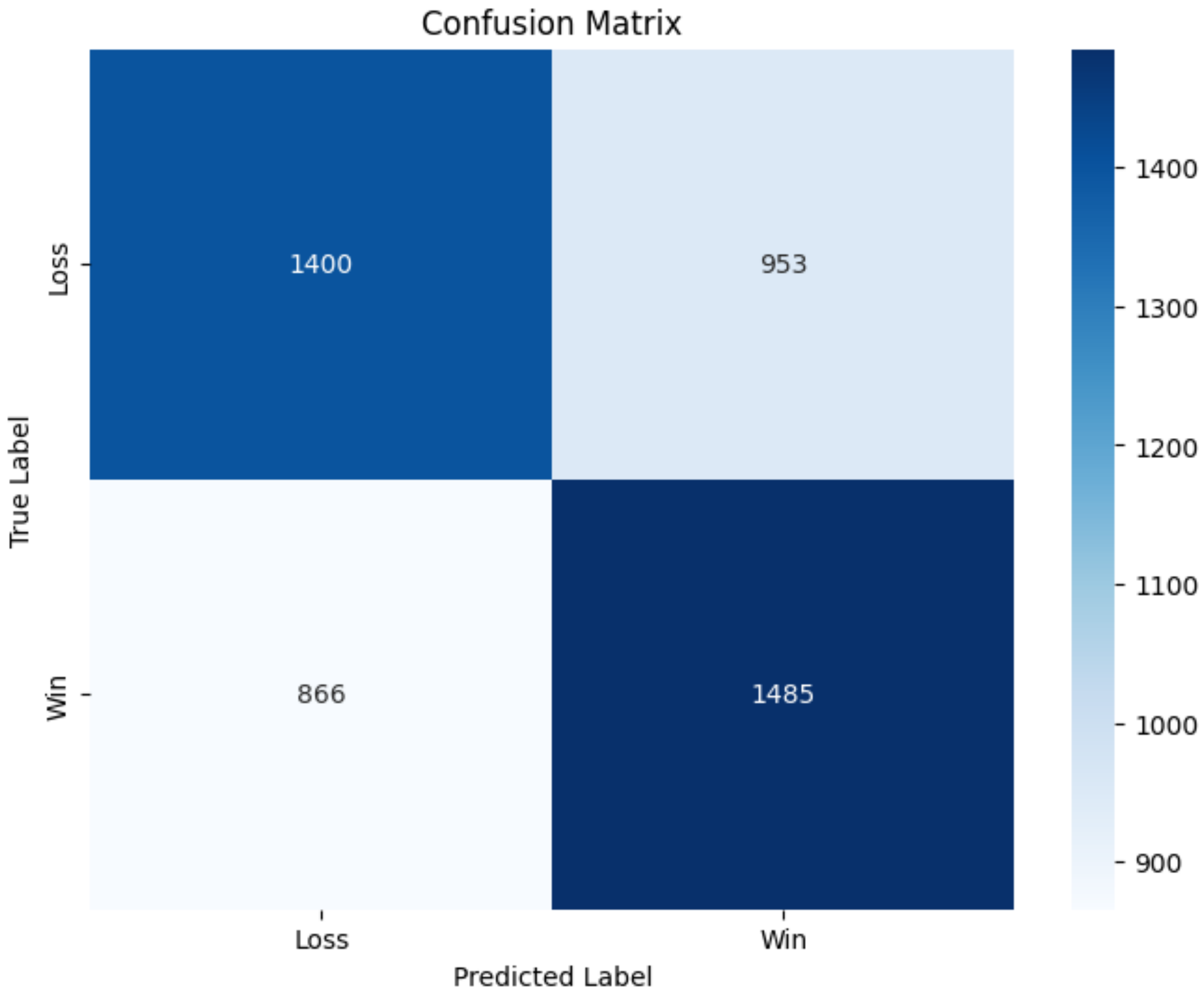
Machine Learning

In [ ]:
```
def backtest(data, model, predictors, start=2, step=1):

    if TRAINING == False:
        raise Exception("Training model is not allowed now")

    all_predictions = []

    seasons = sorted(data["season"].unique())

    for i in range(start, len(seasons), step):
        print(f"Progress: {i-start}/{len(seasons)-start}")
        season = seasons[i]

        train = data[data["season"] < season]
        test = data[data["season"] == season]

        model.fit(train[predictors],train["target"])

        preds = model.predict(test[predictors])

        preds = pd.Series(preds, index=test.index)
        combined= pd.concat([test["target"],preds],axis=1)
        combined.columns = ["actual","prediction"]

        all_predictions.append(combined)

    return pd.concat(all_predictions)
```

In [ ]:
```
def get_predictors(X,y, model, tscv_split=3,n_features_to_select=30):

    if TRAINING == False:
        raise Exception("Training model is not allowed now")

    selected_columns = X.columns

    tscv = TimeSeriesSplit(n_splits=3)

    sfs = SequentialFeatureSelector(model,
                                    n_features_to_select=30,
                                    direction= "forward",
                                    cv=tscv,
                                    n_jobs=1)

    sfs.fit(X, y)
    print("have got predictors")

    return list(selected_columns[sfs.get_support()])
```

In [ ]:
```
rr = RidgeClassifier(alpha =1)

predictors = get_predictors(full[selected_columns_full], full["target"],
predictions = backtest(full,rr, predictors)
print_accuracy(predictions["prediction"], predictions["actual"],"RidgeCla
```

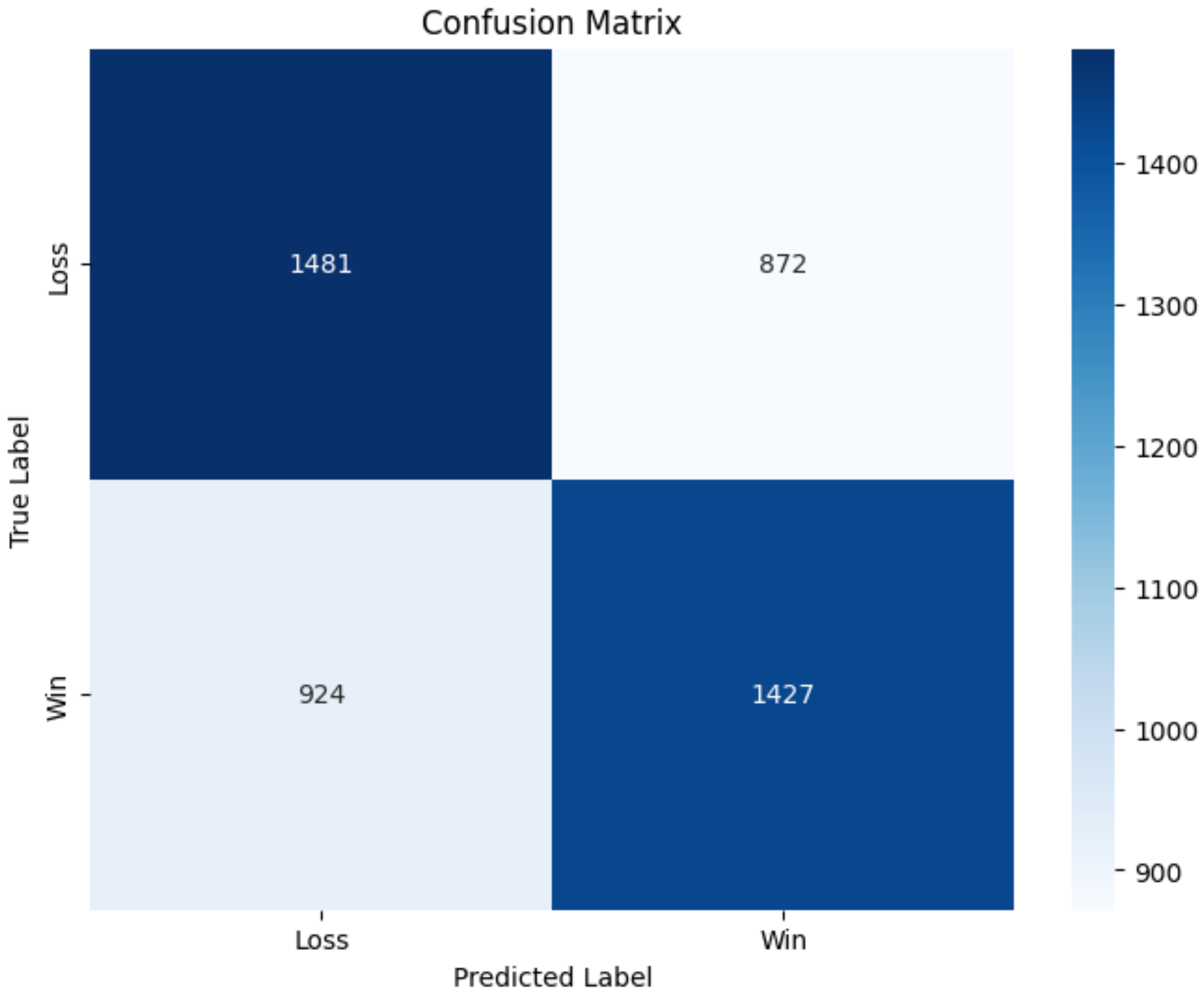
```
have got predictors
Progress: 0/2
Progress: 1/2
This is the result for RidgeClassifier with rolling:
The accuracy score is: 0.6133078231292517
THe MSE is: 0.3866921768707483
```



Random Forest

In [ ]:
```
# Define the model
model = RandomForestClassifier(
    n_estimators=50,
    max_depth=5,
    min_samples_split=3,
    min_samples_leaf=2,
    max_features=0.3,
    random_state=42
)

# Get predictors and train model with rolling
predictors = get_predictors(full[selected_columns_full], full["target"],
predictions = backtest(full, model, predictors)
print_accuracy(predictions["prediction"], predictions["actual"], "Random
```

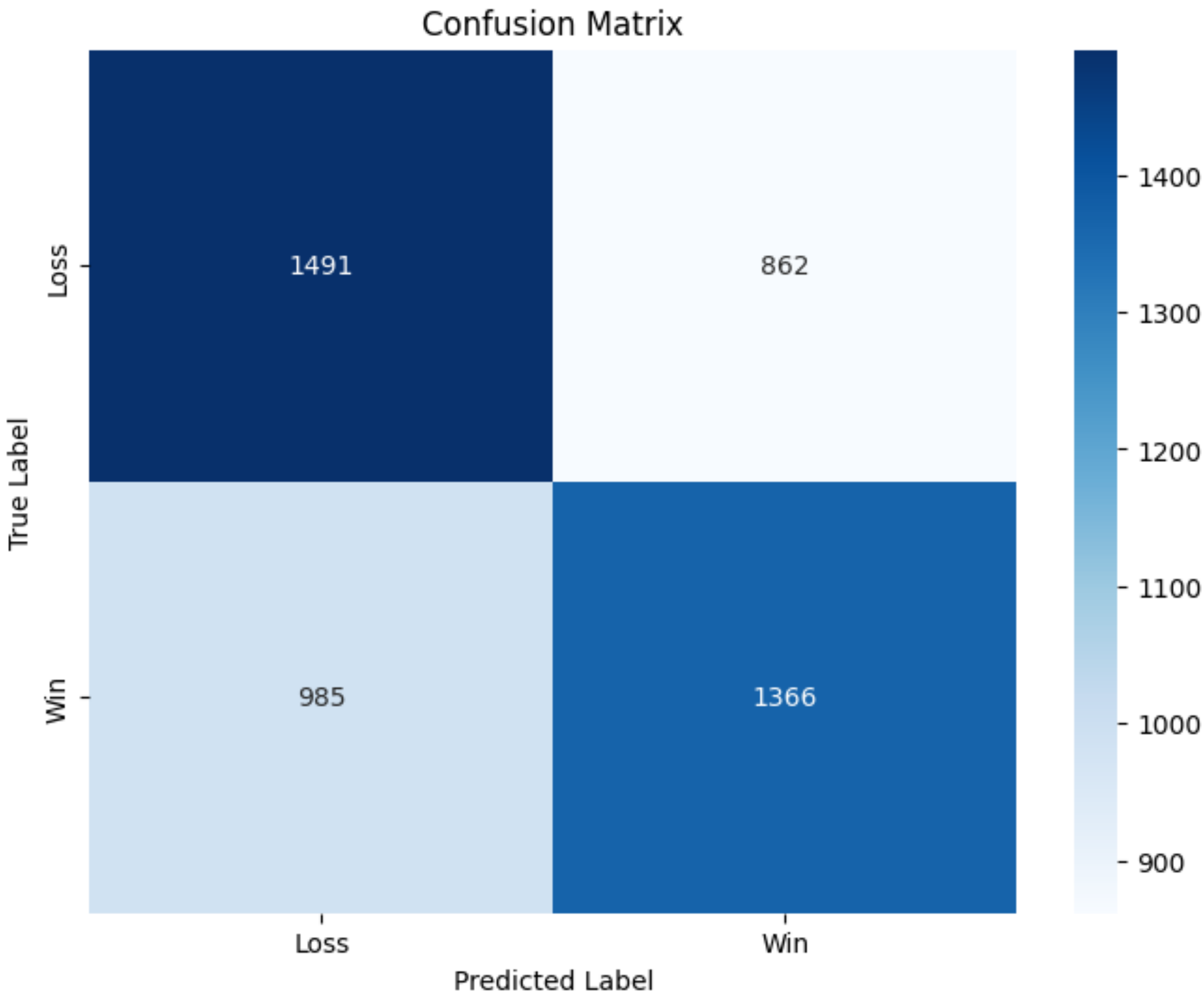
```
have got predictors
Progress: 0/2
Progress: 1/2
This is the result for Random Forest with rolling:
The accuracy score is: 0.6181972789115646
THe MSE is: 0.3818027210884354
```



XGBoost

In [ ]:
```
model = xgb.XGBClassifier(objective = "binary:logistic",
                          learning_rate=0.005,
                          max_depth=3,
                          n_estimators=30,
                          colsample_bytree=0.3,
                          min_child_weight=0.3,
                          reg_alpha=0.3,
                      )

predictors = get_predictors(full[selected_columns_full], full["target"],
predictions = backtest(full,model, predictors)
print_accuracy(predictions["prediction"], predictions["actual"],"XGB with
```

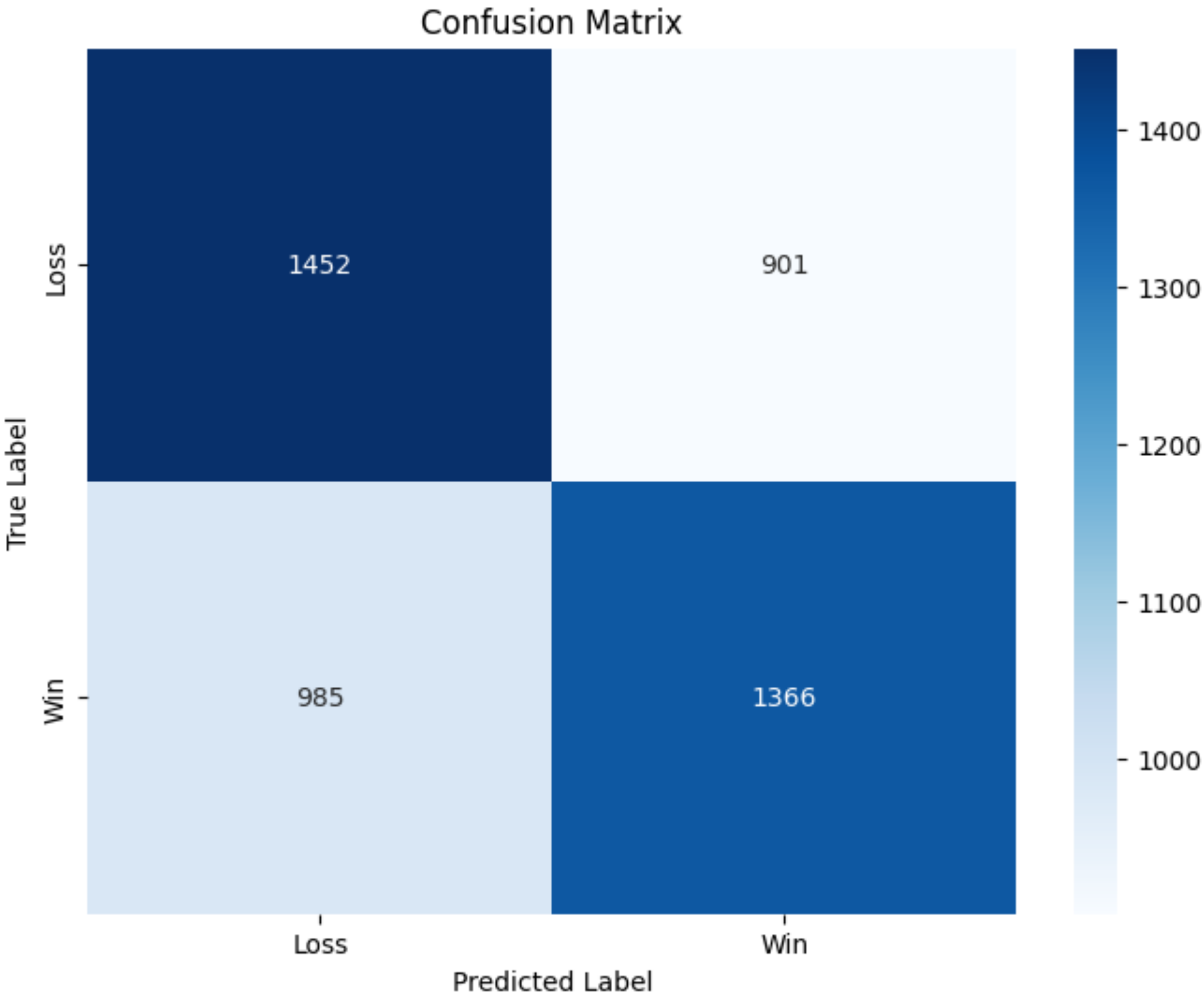
```
have got predictors
Progress: 0/2
Progress: 1/2
This is the result for XGB with rolling:
The accuracy score is: 0.6073554421768708
THe MSE is: 0.39264455782312924
```



LightGBM

In [ ]:
```
model = lgb.LGBMClassifier(
    boosting_type="gbdt",
    num_leaves=15,            # Controls complexity of trees
    max_depth=5,              # Maximum depth of each tree
    learning_rate=0.01,       # Learning rate
    n_estimators=30,         # Number of boosting iterations
    reg_alpha=0.3,            # L1 regularization
    reg_lambda=0.3,           # L2 regularization
    random_state=42,
    force_col_wise=True,
    verbose=-1
)

predictors = get_predictors(full[selected_columns_full], full["target"],
predictions = backtest(full, model, predictors)
print_accuracy(predictions["prediction"], predictions["actual"], "LightGB
```

```
have got predictors
Progress: 0/2
Progress: 1/2
This is the result for LightGBM with rolling:
The accuracy score is: 0.5990646258503401
THe MSE is: 0.40093537414965985
```



LSTM

In [ ]:
```
# Set the number of timesteps to look back
timesteps = 5

# Assuming 'df' is your DataFrame with features and binary target ('resul
X = df[selected_columns_df].values  # Features
y = df['target'].values  # Target (binary outcome)

# # Normalize features
# scaler = StandardScaler()
# X_scaled = scaler.fit_transform(X)

# Prepare data as sequences
X_lstm = []
y_lstm = []

for i in range(timesteps, len(X)):
    X_lstm.append(X[i-timesteps:i])  # Sequence of 5 past games
    y_lstm.append(y[i])

X_lstm, y_lstm = np.array(X_lstm), np.array(y_lstm)

# Initialize TimeSeriesSplit
tscv = TimeSeriesSplit(n_splits=5)
fold = 1
all_fold_accuracies = []

# Iterate through each split
for train_index, val_index in tscv.split(X_lstm):
    X_train, X_val = X_lstm[train_index], X_lstm[val_index]
    y_train, y_val = y_lstm[train_index], y_lstm[val_index]

    # Build a new LSTM model for each fold
    model = Sequential()
    model.add(LSTM(units=64, return_sequences=True, input_shape=(X_train.
    model.add(Dropout(0.2))
    model.add(LSTM(units=32, return_sequences=False))
    model.add(Dropout(0.2))
    model.add(Dense(1, activation='sigmoid'))

    # Compile the model
    model.compile(optimizer=Adam(), loss='binary_crossentropy', metrics=[

    # Train the model on the current training fold
    print(f"Training fold {fold}...")
    history = model.fit(X_train, y_train, epochs=20, batch_size=32, valid

    # Evaluate the model on the validation fold
    val_loss, val_acc = model.evaluate(X_val, y_val, verbose=0)
    print(f"Fold {fold} - Validation Accuracy: {val_acc:.4f}")
    all_fold_accuracies.append(val_acc)
```

```
    fold += 1

# Print average accuracy across folds
print(f"Average validation accuracy across folds: {np.mean(all_fold_accur
```

```
Training fold 1...
/opt/homebrew/lib/python3.9/site-packages/keras/src/layers/rnn/rnn.py:20
4: UserWarning: Do not pass an `input_shape`/`input_dim` argument to a la
yer. When using Sequential models, prefer using an `Input(shape)` object
as the first layer in the model instead.
  super().__init__(**kwargs)
Fold 1 - Validation Accuracy: 0.5013
Training fold 2...
Fold 2 - Validation Accuracy: 0.5142
Training fold 3...
Fold 3 - Validation Accuracy: 0.4939
Training fold 4...
Fold 4 - Validation Accuracy: 0.5027
Training fold 5...
Fold 5 - Validation Accuracy: 0.4960
Average validation accuracy across folds: 0.5016
```

Conclusion

In this project, I evaluated multiple models to predict NBA game results, including RidgeClassifier, Random Forest, XGBoost, LightGBM, and LSTM. RidgeClassifier and Random Forest achieved the highest accuracy, with scores of 0.613 and 0.618, respectively. While Random Forest offers slightly better performance, its computational time is significantly higher, making RidgeClassifier a preferable option for achieving similar results with greater efficiency.

Advanced models like XGBoost and LightGBM yielded around 0.6 accuracy, but their extended computation time may limit practicality. These results suggest room for optimization, potentially by enhancing preprocessing or tuning parameters to accelerate computation without sacrificing accuracy.

The LSTM model, while computationally efficient, achieved only 0.5 accuracy. This suggests that LSTM may not be well-suited to this task or may require adjustments, such as tuning hyperparameters or adding engineered features to better capture sequential patterns.

It also seems likely that the current data may not fully capture the complex patterns needed to accurately predict game outcomes. An accuracy of around 0.6 for most models indicates that there is predictive power, but it's limited. This suggests that either:

1. **Important features are missing**: The data may not include key factors that

strongly influence game outcomes, such as player stats, player injuries, lineup stats, recent performance trends, or other contextual factors that could add predictive strength.

2. **Feature quality needs improvement**: The existing data may benefit from further feature engineering. Creating features that reflect recent team form, specific player contributions, or opponent characteristics might better capture game-specific nuances.

3. **Data quantity**: While 8,898 games is substantial, time-series predictions often benefit from more extensive historical data, especially if this data can include finer-grained information, like specific player stats, game location, and schedule-related factors.

Further Improvement that could be done:
To improve accuracy and efficiency, we could:

- Experiment with feature engineering, such as creating new indicators or aggregating statistics to help capture relevant trends.
- Add more features to capture the patterns needed to predict game results.
- Use dimensionality reduction techniques (like PCA) for models with high complexity to speed up training without significantly compromising accuracy.
- Consider hyperparameter tuning, especially with Random Forest and boosting algorithms, to balance the trade-off between accuracy and computation time.