In [ ]:
```
#Predicting NBA Salaries w/ Gradient Boosting
```

In [1]:
```
import pandas as pd
import numpy as np

# Load data on player stats and salaries
df = pd.read_csv('nba_2022-23_all_stats_with_salary.csv', index_col

# Fill columns with NaN values with zeros
columns_to_fill = ['FT%', '3P%', '2P%', 'eFG%', 'FG%',  '3PAr', 'FT
df[columns_to_fill] = df[columns_to_fill].fillna(0)

# Display first five rows of dataframe
df.head()
```

Out[1]:

	Player Name	Salary	Position	Age	Team	GP	GS	MP	FG	FGA
0	Stephen Curry	48070014	PG	34	GSW	56	56	34.7	10.0	20.2
1	John Wall	47345760	PG	32	LAC	34	3	22.2	4.1	9.9
2	Russell Westbrook	47080179	PG	34	LAL/LAC	73	24	29.1	5.9	13.6
3	LeBron James	44474988	PF	38	LAL	55	54	35.5	11.1	22.2
4	Kevin Durant	44119845	PF	34	BRK/PHO	47	47	35.6	10.3	18.3

5 rows × 51 columns

In [2]:
```
df = df[df['GP'] >= 25]
```

In [ ]:
```
#Feature Selection
```

In [3]:
```
X = df[['Player Name', 'Age','GP', 'GS', 'MP',
       'FG', 'FGA', 'FG%', '3P', '3PA', '3P%', '2P', '2PA', '2P%',
       'FT', 'FTA', 'FT%', 'ORB', 'DRB', 'TRB', 'AST', 'STL', 'BLK'
       'PF', 'PTS', 'PER', 'TS%', '3PAr', 'FTr', 'ORB%',
       'DRB%', 'TRB%', 'AST%', 'STL%', 'BLK%', 'TOV%', 'USG%', 'OWS
       'WS', 'WS/48', 'OBPM', 'DBPM', 'BPM', 'VORP']]



# Target is salary
y = df['Salary']
```

In [4]:
```
from sklearn.feature_selection import mutual_info_regression, Selec
from sklearn.linear_model import LassoCV
```

```
# Calculate the correlation matrix
correlation_matrix = X.drop(['Player Name'], axis=1).corr()

# Find highly correlated features
corr_threshold = 0.8  # Adjust the correlation threshold as needed
correlated_features = set()

for i in range(len(correlation_matrix.columns)):
    for j in range(i):
        if abs(correlation_matrix.iloc[i, j]) > corr_threshold:
            colname_i = correlation_matrix.columns[i]
            colname_j = correlation_matrix.columns[j]
            # Keep one feature and add the other to the set of corr
            if colname_i not in correlated_features:
                correlated_features.add(colname_j)


# Drop the correlated features
X_filtered = X.drop(columns=correlated_features)
X_filtered.drop(['Player Name'], axis=1, inplace=True)

# LASSO Regression for additional feature selection
lasso = LassoCV()
lasso.fit(X_filtered, y)

# Use SelectFromModel to get selected features based on LASSO coeff
sfm = SelectFromModel(lasso, prefit=True)
selected_features_lasso = X_filtered.columns[sfm.get_support()]

# Convert to a DataFrame if needed
selected_features_df = pd.DataFrame(list(selected_features_lasso),

print(selected_features_df)
```

```
   Selected_Features
0                Age
1                 GP
2                3PA
3                3P%
4                TRB
5                STL
6                 PF
7               3PAr
8               TRB%
9               AST%
10              BLK%
11              TOV%
12              USG%
13              DBPM
14              VORP
```

In [ ]:
```
#Train and Evaluate Several ML Models to Predict 2022-23 Salary
```

In [5]:
```
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LinearRegression
```

```
from sklearn.tree import DecisionTreeRegressor
from sklearn.ensemble import RandomForestRegressor, GradientBoostin
from sklearn.svm import SVR
from sklearn.metrics import mean_squared_error, r2_score


# Train-Test Split
train_df, test_df, y_train, y_test = train_test_split(X, y, test_si

X_train = train_df[selected_features_lasso]
X_test = test_df[selected_features_lasso]

# Feature Scaling (Standardization)
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

# Import necessary modules
from sklearn.linear_model import LinearRegression
from sklearn.tree import DecisionTreeRegressor
from sklearn.ensemble import RandomForestRegressor, GradientBoostin
from sklearn.svm import SVR
from sklearn.metrics import mean_squared_error, r2_score

# Define and Train Regression Models
models = [
    ('Linear Regression', LinearRegression()),
    ('Decision Tree Regressor', DecisionTreeRegressor(random_state=
    ('Random Forest Regressor', RandomForestRegressor(random_state=
    ('Support Vector Regressor', SVR(kernel='linear')),
    ('Gradient Boosting Regressor', GradientBoostingRegressor(rando
]

for model_name, model in models:
    # Fit the model
    model.fit(X_train_scaled, y_train)

    # Make predictions
    y_pred = model.predict(X_test_scaled)

    # Calculate MSE and R2
    mse = mean_squared_error(y_test, y_pred)
    r2 = r2_score(y_test, y_pred)

    # Print results
    print(f'Model: {model_name}')
    print(f'Mean Squared Error (MSE): {mse:.4f}')
    print(f'R-squared (R2): {r2:.4f}')
    print('---')
```

```
Model: Linear Regression
Mean Squared Error (MSE): 37576458850299.9844
R-squared (R2): 0.7589
---
Model: Decision Tree Regressor
Mean Squared Error (MSE): 80011688192916.5156
R-squared (R2): 0.4866
---
Model: Random Forest Regressor
Mean Squared Error (MSE): 39549458189751.7266
R-squared (R2): 0.7462
---
Model: Support Vector Regressor
Mean Squared Error (MSE): 199751026808638.9062
R-squared (R2): -0.2818
---
Model: Gradient Boosting Regressor
Mean Squared Error (MSE): 35154571673973.5273
R-squared (R2): 0.7744
---
```

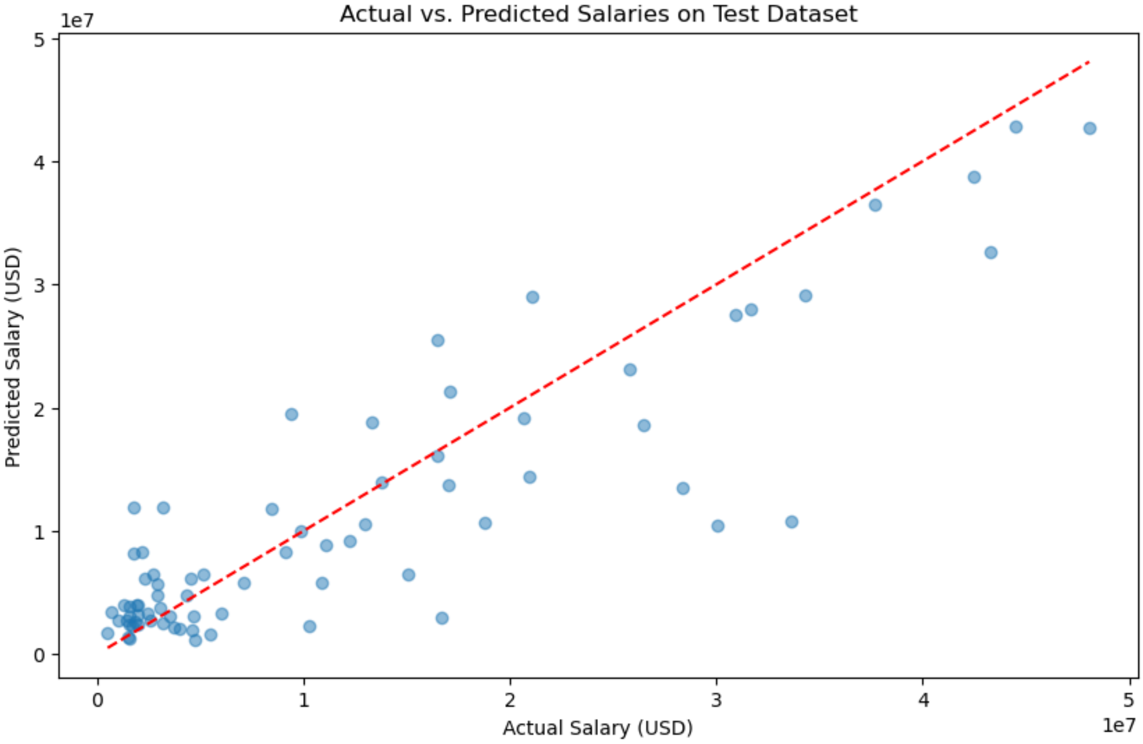
In [10]:

```
#Re-training Gradient Boosting Regressor
```

In [6]:

```
import matplotlib.pyplot as plt
from sklearn.ensemble import RandomForestRegressor
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import mean_squared_error, r2_score


# Feature Scaling (Standardization)
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

# Retrain the GB Regressor on the full training data
rf_model =  GradientBoostingRegressor(random_state=42)
rf_model.fit(X_train_scaled, y_train)

# Make predictions on the test set
y_pred = rf_model.predict(X_test_scaled)

# Calculate MSE and R2 on the test set
mse = mean_squared_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)

# Get predictions, actual values, and player names for the test set
predictions_df = pd.DataFrame({
    'Player Name': test_df['Player Name'],
    'Actual Salary': y_test,
    'Predicted Salary': y_pred
})

# Plot actual vs. predicted salaries
plt.figure(figsize=(10, 6))
plt.scatter(y_test, y_pred, alpha=0.5)
plt.title('Actual vs. Predicted Salaries on Test Dataset')
```

```
plt.xlabel('Actual Salary (USD)')
plt.ylabel('Predicted Salary (USD)')
plt.plot([min(y_test), max(y_test)], [min(y_test), max(y_test)], li


plt.show()

# Print MSE and R2
print(f'Mean Squared Error (MSE): {mse:.4f}')
print(f'R-squared (R2): {r2:.4f}')
```

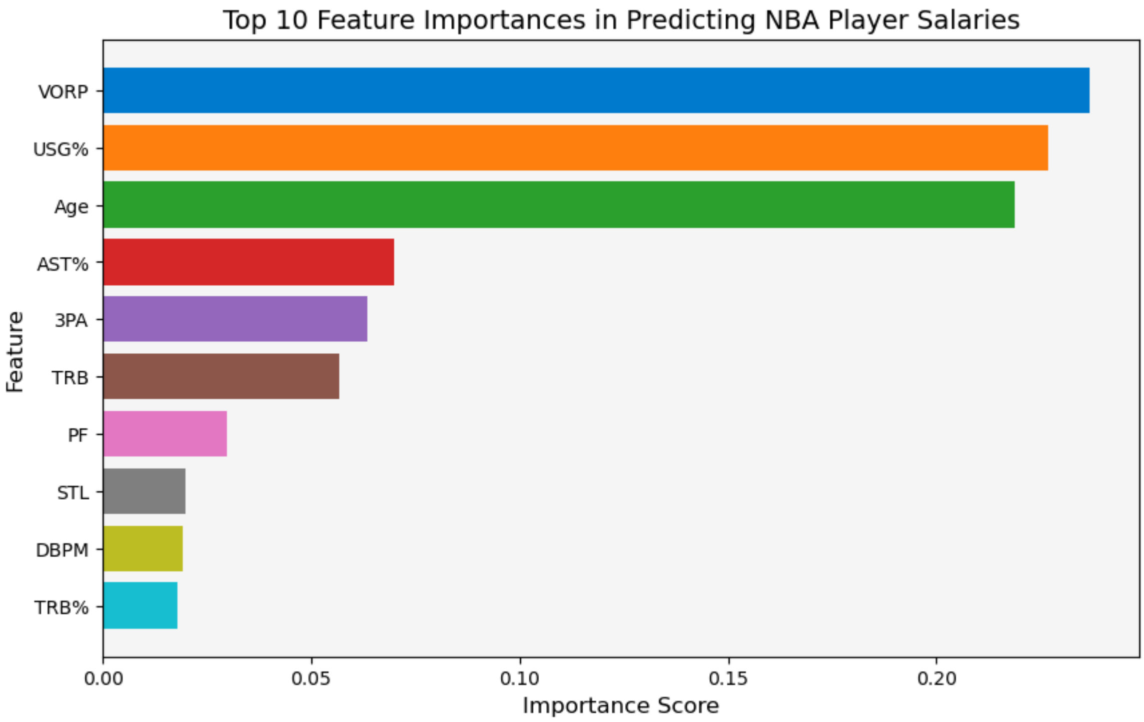



```
Mean Squared Error (MSE): 35154571673973.5273
R-squared (R2): 0.7744
```

Visualising Feature Importance

In [7]:
```
# Get feature importances from the trained Random Forest model
feature_importances = rf_model.feature_importances_

# Create a DataFrame to associate feature names with their importan
importance_df = pd.DataFrame({'Feature': X_train.columns, 'Importan

# Sort the features by importance in descending order
importance_df = importance_df.sort_values(by='Importance', ascendin

# Set a stylish color palette
colors = ['#007acc', '#ff7f0e', '#2ca02c', '#d62728', '#9467bd', '#

# Create an eye-catching horizontal bar chart
plt.figure(figsize=(10, 6))
plt.barh(importance_df['Feature'][:10], importance_df['Importance']
plt.title('Top 10 Feature Importances in Predicting NBA Player Sala
plt.xlabel('Importance Score', fontsize=12)
```

```
plt.ylabel('Feature', fontsize=12)
plt.gca().invert_yaxis()  # Invert the y-axis to show the most impo

# Add a cool background
ax = plt.gca()
ax.set_facecolor('#f5f5f5')

plt.show()
```



Exploring Overpaid Players in the Test Dataset

In [8]:

```
# Calculate absolute and percentage difference between actual salar
predictions_df['Absolute Difference'] = predictions_df['Actual Sala
predictions_df['Percentage Difference'] = (predictions_df['Absolute

predictions_df.head()
```

Out[8]:

	Player Name	Actual Salary	Predicted Salary	Absolute Difference	Percentage Difference
203	Jalen Smith	4670160	3.038670e+06	1.631490e+06	53.690930
34	Shai Gilgeous-Alexander	30913750	2.753312e+07	3.380628e+06	12.278403
15	Jimmy Butler	37653300	3.653262e+07	1.120683e+06	3.067624
331	Jalen McDaniels	1930681	3.977297e+06	-2.046616e+06	-51.457464
58	Aaron Gordon	20690909	1.918627e+07	1.504635e+06	7.842245

In [9]:

```
predictions_df.sort_values(by='Percentage Difference', ascending=Fa
```

Out[9]:

	Player Name	Actual Salary	Predicted Salary	Absolute Difference	Percentage Difference
78	Collin Sexton	16700000	2.956043e+06	1.374396e+07	464.944337
118	Mo Bamba	10300000	2.265138e+06	8.034862e+06	354.718471
202	Ty Jerome	4728948	1.138166e+06	3.590782e+06	315.488525
186	Dyson Daniels	5508600	1.627977e+06	3.880623e+06	238.370964
26	Andrew Wiggins	33616770	1.078876e+07	2.282801e+07	211.590538

In [ ]: