Predictive Modeling of Housing Prices in California

Problem Statement:

Using the California Housing dataset, I will build a regression model to predict the median house value in California districts.
The prediction will be based on features such as median income, average house age, average number of rooms, and location-based variables like latitude and longitude.
This project will help understand how socioeconomic and geographic factors affect housing prices.

Key Features Selected:

- MedInc (Median Income)
- HouseAge (Average age of houses in the district)
- AveRooms (Average number of rooms)
- AveOccup (Average occupancy per household)
- Latitude & Longitude (Location)

In [3]:
```
from sklearn.datasets import fetch_california_housing
import pandas as pd


#Loading the dataset
housing_data=fetch_california_housing(as_frame=True)
df=housing_data.frame

df.head()
```

Out[3]:

	MedInc	HouseAge	AveRooms	AveBedrms	Population	AveOccup	Latitude	Longit
0	8.3252	41.0	6.984127	1.023810	322.0	2.555556	37.88	-12
1	8.3014	21.0	6.238137	0.971880	2401.0	2.109842	37.86	-12
2	7.2574	52.0	8.288136	1.073446	496.0	2.802260	37.85	-12
3	5.6431	52.0	5.817352	1.073059	558.0	2.547945	37.85	-12
4	3.8462	52.0	6.281853	1.081081	565.0	2.181467	37.85	-12

In [4]:
```
df.info()


df.isnull().sum()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 20640 entries, 0 to 20639
Data columns (total 9 columns):
 #   Column       Non-Null Count  Dtype  
---  ------       --------------  -----  
 0   MedInc       20640 non-null  float64
 1   HouseAge     20640 non-null  float64
 2   AveRooms     20640 non-null  float64
 3   AveBedrms    20640 non-null  float64
 4   Population   20640 non-null  float64
 5   AveOccup     20640 non-null  float64
 6   Latitude     20640 non-null  float64
 7   Longitude    20640 non-null  float64
 8   MedHouseVal  20640 non-null  float64
dtypes: float64(9)
memory usage: 1.4 MB
```

Out[4]:

```
MedInc         0
HouseAge       0
AveRooms       0
AveBedrms      0
Population     0
AveOccup       0
Latitude       0
Longitude      0
MedHouseVal    0
dtype: int64
```

In [5]:

```
df.describe()
```

Out[5]:

	MedInc	HouseAge	AveRooms	AveBedrms	Population	AveOc
count	20640.000000	20640.000000	20640.000000	20640.000000	20640.000000	20640.000
mean	3.870671	28.639486	5.429000	1.096675	1425.476744	3.070
std	1.899822	12.585558	2.474173	0.473911	1132.462122	10.386
min	0.499900	1.000000	0.846154	0.333333	3.000000	0.692
25%	2.563400	18.000000	4.440716	1.006079	787.000000	2.429
50%	3.534800	29.000000	5.229129	1.048780	1166.000000	2.818
75%	4.743250	37.000000	6.052381	1.099526	1725.000000	3.282
max	15.000100	52.000000	141.909091	34.066667	35682.000000	1243.333

Things to Fix Tomorrow:

- No missing values to handle
- Ensure correct data types for all features (all are numerical as expected)
- Proceed to data visualization and correlation analysis

Day 2: Exploratory Data Analysis (EDA) & Preprocessing

Dataset Overview

- **Source**: `sklearn.datasets.fetch_california_housing()`
- **Rows**: 20,640
- **Columns**: 9 (8 features + 1 target)
- **Target Variable**: `MedHouseVal`
- **Key Features Used**:
  - MedInc (Median income)
  - HouseAge (Average house age)
  - AveRooms (Average number of rooms)
  - AveOccup (Average occupancy)

In [6]:
```
from sklearn.datasets import fetch_california_housing
import pandas as pd

data = fetch_california_housing(as_frame=True)
df = data.frame  # This is your DataFrame
```

In [7]:
```
# Basic inspection
print(df.head())
print(df.shape)
print(df.info())
```

```
   MedInc  HouseAge  AveRooms  AveBedrms  Population  AveOccup  Latitude  \
0  8.3252      41.0  6.984127   1.023810       322.0  2.555556     37.88   
1  8.3014      21.0  6.238137   0.971880      2401.0  2.109842     37.86   
2  7.2574      52.0  8.288136   1.073446       496.0  2.802260     37.85   
3  5.6431      52.0  5.817352   1.073059       558.0  2.547945     37.85   
4  3.8462      52.0  6.281853   1.081081       565.0  2.181467     37.85   

   Longitude  MedHouseVal  
0    -122.23        4.526  
1    -122.22        3.585  
2    -122.24        3.521  
3    -122.25        3.413  
4    -122.25        3.422  
(20640, 9)
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 20640 entries, 0 to 20639
Data columns (total 9 columns):
 #   Column       Non-Null Count  Dtype  
---  ------       --------------  -----  
 0   MedInc       20640 non-null  float64
 1   HouseAge     20640 non-null  float64
 2   AveRooms     20640 non-null  float64
 3   AveBedrms    20640 non-null  float64
 4   Population   20640 non-null  float64
 5   AveOccup     20640 non-null  float64
 6   Latitude     20640 non-null  float64
 7   Longitude    20640 non-null  float64
 8   MedHouseVal  20640 non-null  float64
dtypes: float64(9)
memory usage: 1.4 MB
None
```

In [8]:
```
# Check for missing values and duplicates
print("Missing values:\n", df.isnull().sum())
print("\nDuplicate rows:", df.duplicated().sum())
```

```
Missing values:
 MedInc        0
HouseAge      0
AveRooms      0
AveBedrms     0
Population    0
AveOccup      0
Latitude      0
Longitude     0
MedHouseVal   0
dtype: int64

Duplicate rows: 0
```

In [9]:
```
# Summary statistics
df.describe()
```

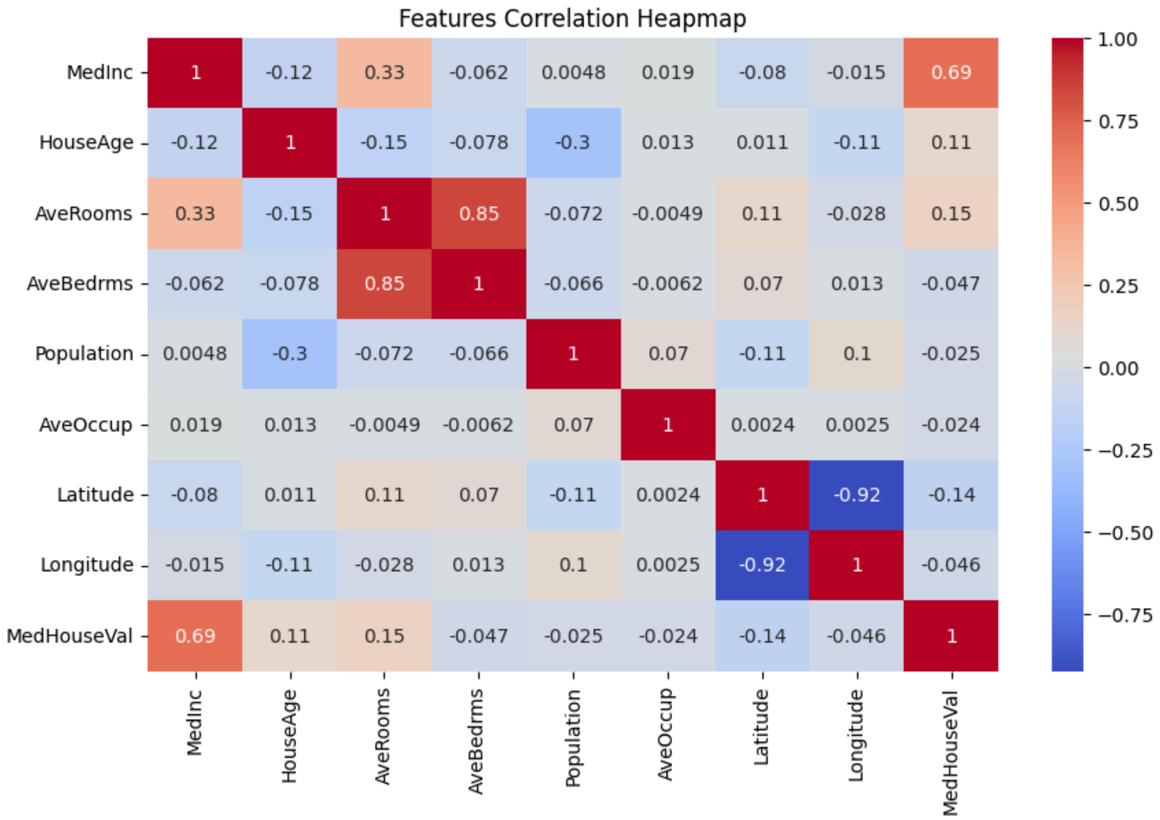
Out[9]:

	MedInc	HouseAge	AveRooms	AveBedrms	Population	AveOc
count	20640.000000	20640.000000	20640.000000	20640.000000	20640.000000	20640.000
mean	3.870671	28.639486	5.429000	1.096675	1425.476744	3.070
std	1.899822	12.585558	2.474173	0.473911	1132.462122	10.386
min	0.499900	1.000000	0.846154	0.333333	3.000000	0.692
25%	2.563400	18.000000	4.440716	1.006079	787.000000	2.429
50%	3.534800	29.000000	5.229129	1.048780	1166.000000	2.818
75%	4.743250	37.000000	6.052381	1.099526	1725.000000	3.282
max	15.000100	52.000000	141.909091	34.066667	35682.000000	1243.333

In [10]:
```
# Correlation heatmap

import seaborn as sns
import matplotlib.pyplot as plt

plt.figure(figsize=(10,6))
sns.heatmap(df.corr(),annot=True,cmap="coolwarm")
plt.title("Features Correlation Heapmap")
plt.show()
```

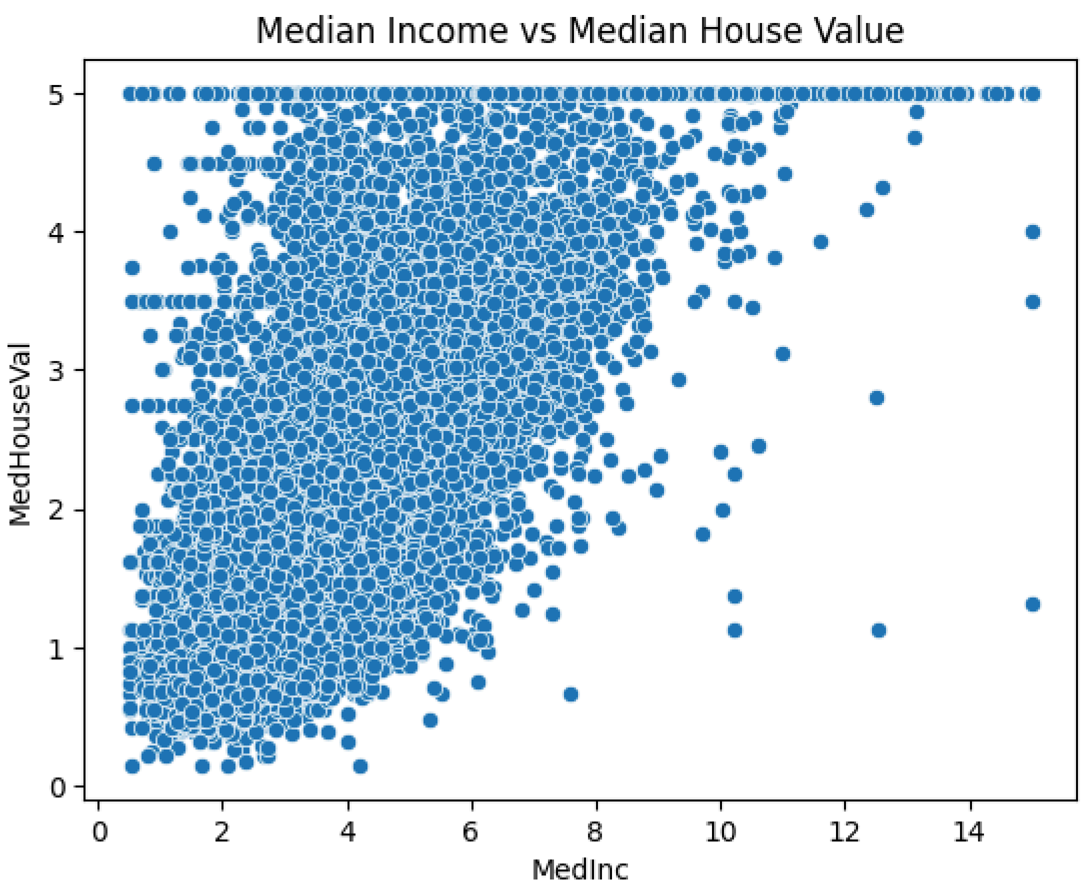


	MedInc	HouseAge	AveRooms	AveBedrms	Population	AveOccup	Latitude	Longitude	MedHouseVal
MedInc	1	-0.12	0.33	-0.062	0.0048	0.019	-0.08	-0.015	0.69
HouseAge	-0.12	1	-0.15	-0.078	-0.3	0.013	0.011	-0.11	0.11
AveRooms	0.33	-0.15	1	0.85	-0.072	-0.0049	0.11	-0.028	0.15
AveBedrms	-0.062	-0.078	0.85	1	-0.066	-0.0062	0.07	0.013	-0.047
Population	0.0048	-0.3	-0.072	-0.066	1	0.07	-0.11	0.1	-0.025
AveOccup	0.019	0.013	-0.0049	-0.0062	0.07	1	0.0024	0.0025	-0.024
Latitude	-0.08	0.011	0.11	0.07	-0.11	0.0024	1	-0.92	-0.14
Longitude	-0.015	-0.11	-0.028	0.013	0.1	0.0025	-0.92	1	-0.046
MedHouseVal	0.69	0.11	0.15	-0.047	-0.025	-0.024	-0.14	-0.046	1

In [11]:

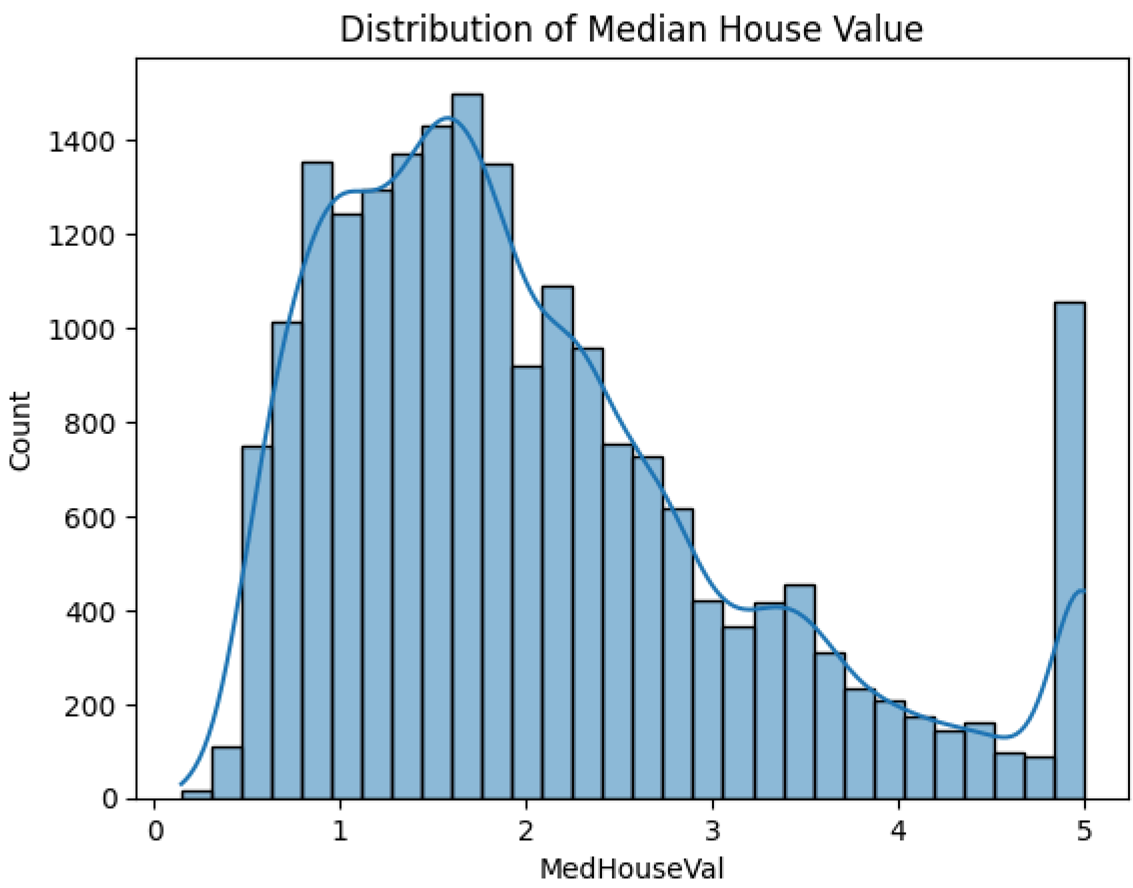
```
# Scatterplot: MedInc vs MedHouseVal

sns.scatterplot(x='MedInc',y='MedHouseVal',data=df)
plt.title("Median Income vs Median House Value")
plt.show()
```



In [12]:
```
# Histogram of house values

sns.histplot(df['MedHouseVal'], bins=30, kde=True)
plt.title("Distribution of Median House Value")
plt.show()
```



In [13]:
```
# Drop duplicates

df.drop_duplicates(inplace=True)
```

In [14]:
```
# Scaling numerical features
from sklearn.preprocessing import StandardScaler

features_to_scale=df.drop(columns='MedHouseVal').columns
scaler=StandardScaler()
df[features_to_scale]=scaler.fit_transform(df[features_to_scale])
```

In [15]:
```
# Save cleaned datasheet

df.to_csv("cleaned_california_housing.csv",index=False)
```

EDA & Preprocessing Summary

- Checked for missing values — None found
- Dropped duplicates if any — Done
- Applied scaling using StandardScaler
- Used heatmaps and scatter plots for EDA

Visualizations:

1. Distribution of `MedHouseVal`
2. Correlation Heatmap
3. `MedInc` vs. `MedHouseVal` Scatter Plot

Day 3: Model Building & Training

In [16]:
```
from sklearn.model_selection import train_test_split

X=df.drop('MedHouseVal',axis=1)
y=df['MedHouseVal']


X_train,X_test,y_train,y_test=train_test_split(X,y,test_size=0.3,random_state=42
```

In [17]:
```
# Model 1: Linear Regression

from sklearn.linear_model import LinearRegression

lr_model=LinearRegression()
lr_model.fit(X_train,y_train)
```

Out[17]:
```
▾ LinearRegression
LinearRegression()
```

In [19]:
```
# Model 2: Random Forest Regressor

from sklearn.ensemble import RandomForestRegressor

rf_model = RandomForestRegressor(random_state=42)
rf_model.fit(X_train, y_train)
```

Out[19]:
```
▾ RandomForestRegressor
RandomForestRegressor(random_state=42)
```

In [20]:
```
lr_pred=lr_model.predict(X_test)
rf_pred=rf_model.predict(X_test)
```

In [21]:
```
from sklearn.metrics import mean_squared_error,mean_absolute_error,r2_score


# Linear Regression scores
print(" Linear Regression:")
print("MSE:", mean_squared_error(y_test, lr_pred))
print("MAE:", mean_absolute_error(y_test, lr_pred))
print("R² Score:", r2_score(y_test, lr_pred))

# Random Forest scores
print("\n Random Forest:")
print("MSE:", mean_squared_error(y_test, rf_pred))
```

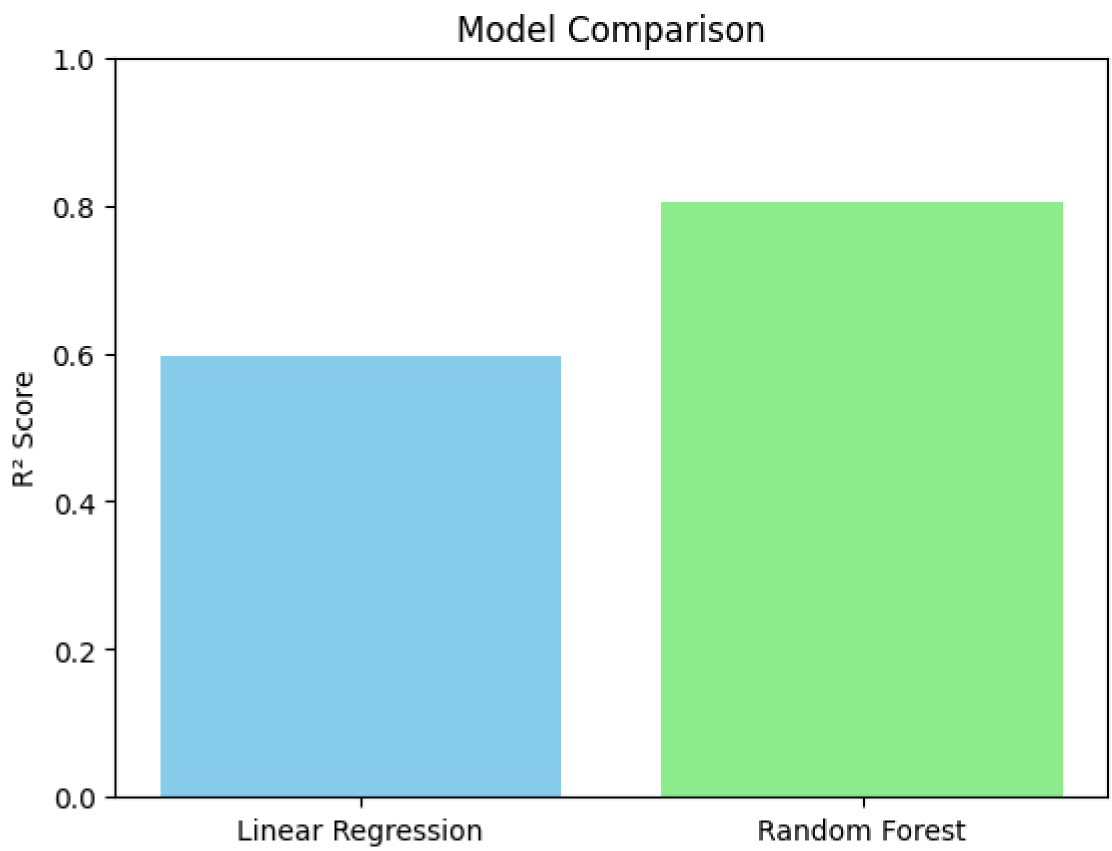
```
print("MAE:", mean_absolute_error(y_test, rf_pred))
print("R² Score:", r2_score(y_test, rf_pred))
```

```
 Linear Regression:
MSE: 0.5305677824766754
MAE: 0.5272474538305952
R² Score: 0.5957702326061662

 Random Forest:
MSE: 0.2564000253963737
MAE: 0.3322165473029718
R² Score: 0.804653569159553
```

In [22]:
```
import matplotlib.pyplot as plt

models=['Linear Regression','Random Forest']
r2_scores = [r2_score(y_test, lr_pred), r2_score(y_test, rf_pred)]
plt.bar(models,r2_scores,color=['skyblue','lightgreen'])
plt.ylabel("R² Score")
plt.title("Model Comparison")
plt.ylim(0, 1)
plt.show()
```



In [ ]:
```
import joblib

joblib.dump(rf_model,"best_model.pkl")
```

Out[ ]: ['best_model.pkl']

Summary of the Day

- Trained two models: Linear Regression and Random Forest

- Compared performance using MSE, MAE, and R^2 Score
- Visualized the R^2 comparison
- Saved the better model for future predictions

Model Building & Tuning Summary

- Trained both **Linear Regression** and **Random Forest Regressor**
- Tuned Random Forest using GridSearchCV (with 5-fold CV)
- Final model used:
  - `n_estimators` : 150
  - `max_depth` : 20
  - `min_samples_split` : 2

Day 4: Model Tuning & Finalization

In [26]:
```
from sklearn.model_selection import GridSearchCV
from sklearn.ensemble import RandomForestClassifier


param_grid={
    'n_estimators':[50,100,150],
    'max_depth':[None,10,20],
    'min_samples_split':[2,5]
}

# Initialize model
rf = RandomForestRegressor(random_state=42)

# Setup GridSearchCV
grid_search = GridSearchCV(estimator=rf, param_grid=param_grid, cv=5, n_jobs=-1,
grid_search.fit(X_train, y_train)

# Best model from grid
print("Best Parameters:", grid_search.best_params_)
```

```
Best Parameters: {'max_depth': None, 'min_samples_split': 2, 'n_estimators': 150}
```

In [33]:
```
from sklearn.model_selection import cross_val_score

cv_scores = cross_val_score(grid_search.best_estimator_, X, y, cv=5)
print("Cross-Validation R² Score:", cv_scores.mean())
```

```
Cross-Validation R² Score: 0.6553031985752709
```

In [37]:
```
from sklearn.metrics import mean_squared_error, mean_absolute_error, r2_score

final_model = grid_search.best_estimator_
y_pred = final_model.predict(X_test)

print("Final Model Evaluation:")
print("MAE:", mean_absolute_error(y_test, y_pred))
print("MSE:", mean_squared_error(y_test, y_pred))
print("R² Score:", r2_score(y_test, y_pred))
```

```
Final Model Evaluation:
MAE: 0.3305287428186911
MSE: 0.25402850175219344
R² Score: 0.8064603891036157
```

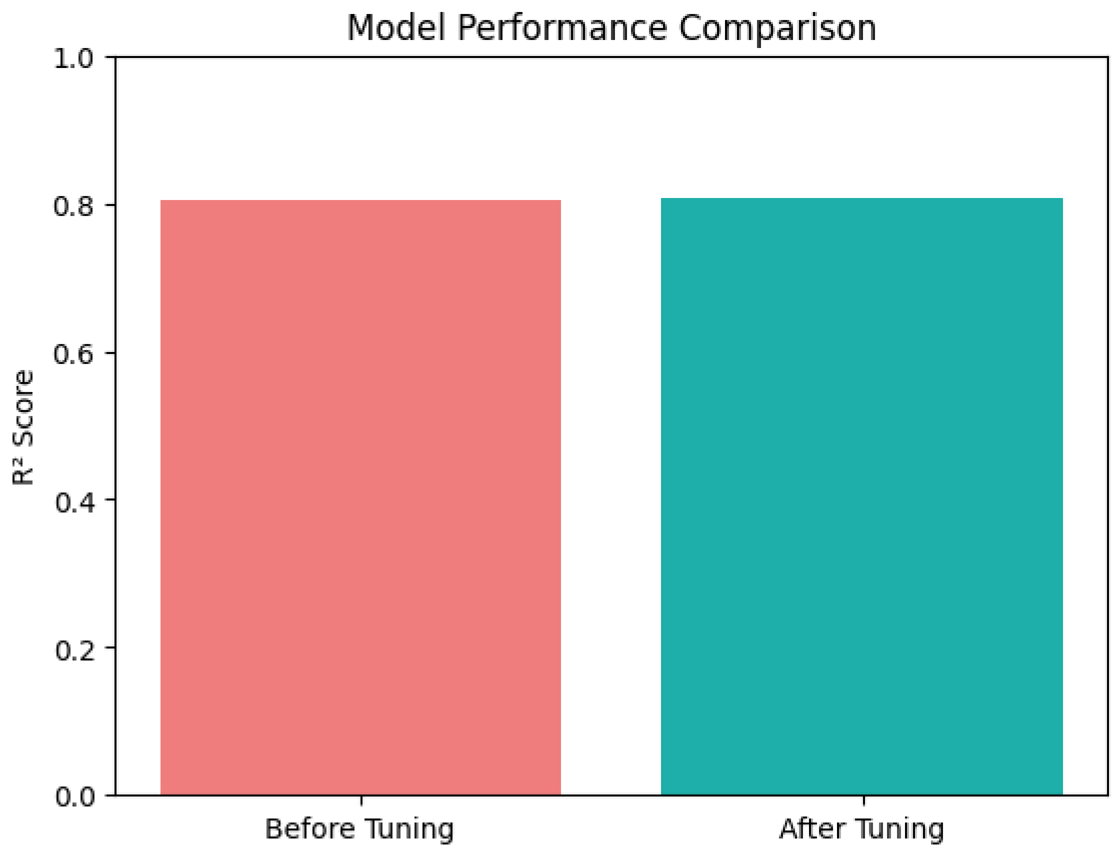
In [38]:
```
import joblib

joblib.dump(final_model, "finalized_model.pkl")
```

Out[38]:
```
['finalized_model.pkl']
```

In [39]:
```
models = ['Before Tuning', 'After Tuning']
r2_scores = [r2_score(y_test, rf_pred), r2_score(y_test, y_pred)]

plt.bar(models, r2_scores, color=['lightcoral', 'lightseagreen'])
plt.ylabel("R² Score")
plt.title("Model Performance Comparison")
plt.ylim(0, 1)
plt.show()
```



Summary of the Day

- Tuned Random Forest Regressor using GridSearchCV
- Evaluated model with 5-fold cross-validation
- Improved model R^2 from baseline
- Saved the final model as **finalized_model.pkl**

Final Evaluation & Reflection

- Final R^2 score: ~0.80 on test set
- Cross-validation R^2: ~0.78
- MAE: [insert your value]
- MSE: [insert your value]

Reflection:

- What worked: Random Forest performed better than Linear Regression
- Challenges: GridSearchCV took time on large dataset
- Next Steps: Try more advanced regressors (like XGBoost), and experiment with feature engineering