House Price Prediction with Supervised Learning AI Model

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.datasets import fetch_california_housing
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
from sklearn.metrics import mean_squared_error, r2_score
```

```
house_price_data = fetch_california_housing()

# Create a pandas DataFrame
df = pd.DataFrame(house_price_data.data, columns=house_price_data.feature_names)
df['MedHouseVal'] = house_price_data.target
```

```
# Display basic information
print("Dataset shape:", df.shape)
print("\nFirst 5 rows:")
display(df.head())
```

```
Dataset shape: (20640, 9)

First 5 rows:
```

	MedInc	HouseAge	AveRooms	AveBedrms	Population	AveOccup	Latitude	Longitude	MedHouseVal
0	8.3252	41.0	6.984127	1.023810	322.0	2.555556	37.88	-122.23	4.526
1	8.3014	21.0	6.238137	0.971880	2401.0	2.109842	37.86	-122.22	3.585
2	7.2574	52.0	8.288136	1.073446	496.0	2.802260	37.85	-122.24	3.521
3	5.6431	52.0	5.817352	1.073059	558.0	2.547945	37.85	-122.25	3.413
4	3.8462	52.0	6.281853	1.081081	565.0	2.181467	37.85	-122.25	3.422

```
# Dataset description
print(house_price_data.DESCR)
```

```
.. _california_housing_dataset:

California Housing dataset
--------------------------

**Data Set Characteristics:**

:Number of Instances: 20640

:Number of Attributes: 8 numeric, predictive attributes and the target

:Attribute Information:
    - MedInc        median income in block group
    - HouseAge      median house age in block group
    - AveRooms      average number of rooms per household
    - AveBedrms     average number of bedrooms per household
    - Population    block group population
    - AveOccup      average number of household members
    - Latitude      block group latitude
    - Longitude     block group longitude

:Missing Attribute Values: None

This dataset was obtained from the StatLib repository.
https://www.dcc.fc.up.pt/~ltorgo/Regression/cal_housing.html

The target variable is the median house value for California districts,
expressed in hundreds of thousands of dollars ($100,000).

This dataset was derived from the 1990 U.S. census, using one row per census
block group. A block group is the smallest geographical unit for which the U.S.
Census Bureau publishes sample data (a block group typically has a population
of 600 to 3,000 people).

A household is a group of people residing within a home. Since the average
number of rooms and bedrooms in this dataset are provided per household, these
columns may take surprisingly large values for block groups with few households
and many empty houses, such as vacation resorts.

It can be downloaded/loaded using the
:func:`sklearn.datasets.fetch_california_housing` function.

.. rubric:: References

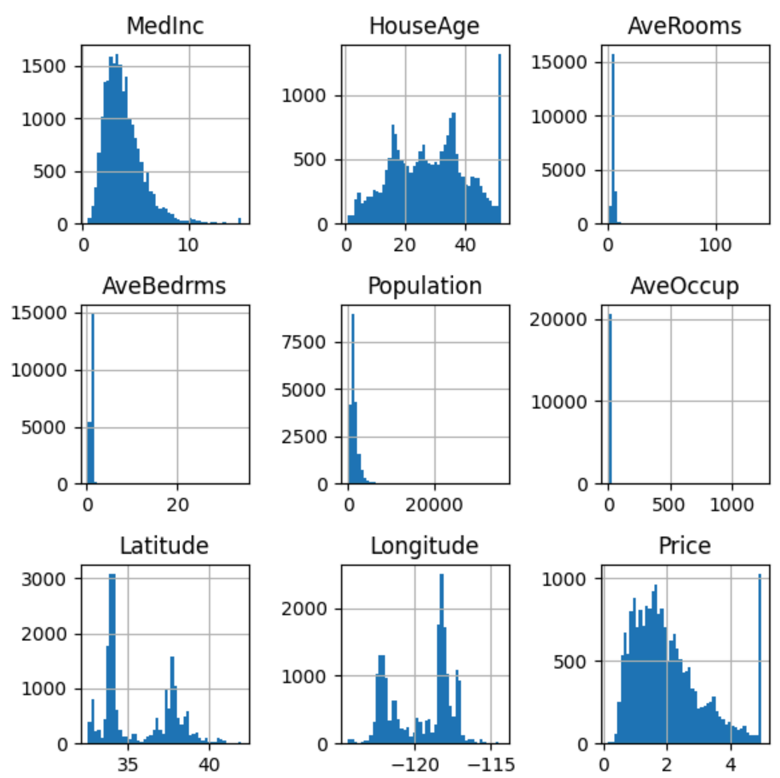
- Pace, R. Kelley and Ronald Barry, Sparse Spatial Autoregressions,
  Statistics and Probability Letters, 33 (1997) 291-297
```

```
# Basic statistics
display(df.describe().T)
```

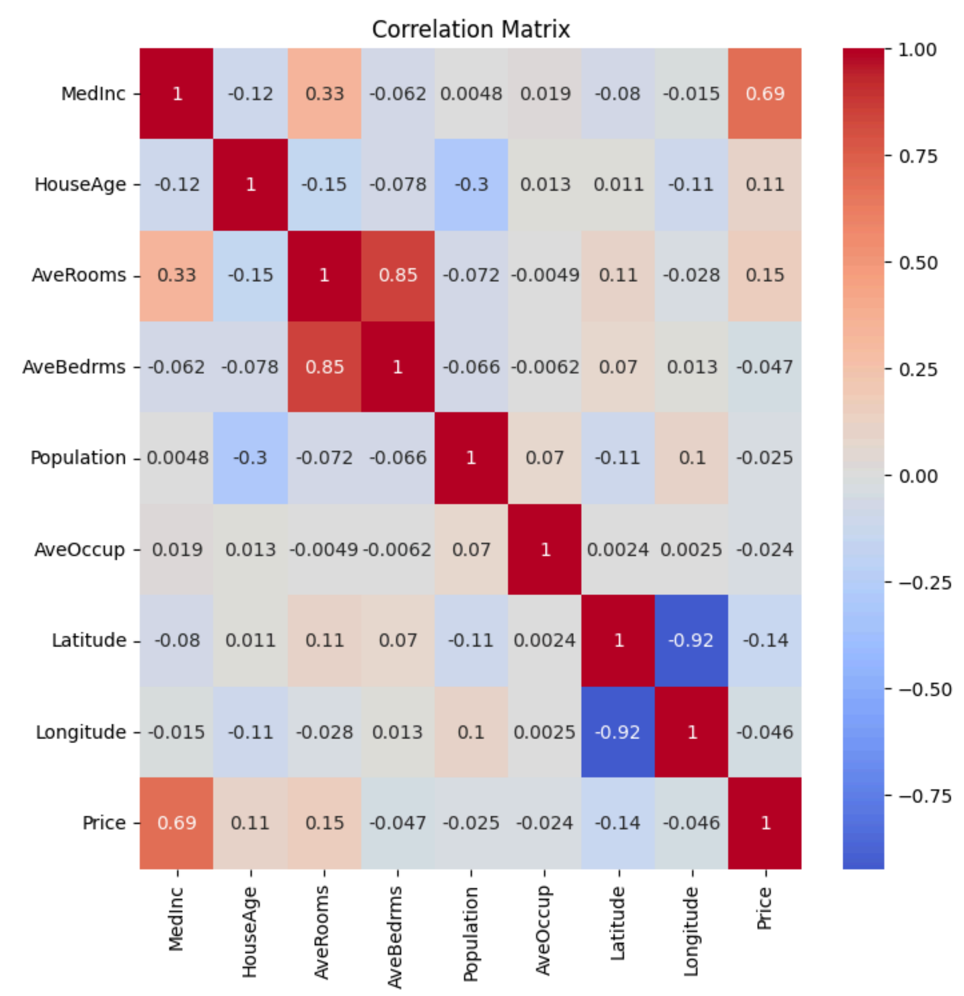
	count	mean	std	min	25%	50%	75%	max
MedInc	20640.0	3.870671	1.899822	0.499900	2.563400	3.534800	4.743250	15.000100
HouseAge	20640.0	28.639486	12.585558	1.000000	18.000000	29.000000	37.000000	52.000000
AveRooms	20640.0	5.429000	2.474173	0.846154	4.440716	5.229129	6.052381	141.909091
AveBedrms	20640.0	1.096675	0.473911	0.333333	1.006079	1.048780	1.099526	34.066667
Population	20640.0	1425.476744	1132.462122	3.000000	787.000000	1166.000000	1725.000000	35682.000000
AveOccup	20640.0	3.070655	10.386050	0.692308	2.429741	2.818116	3.282261	1243.333333
Latitude	20640.0	35.631861	2.135952	32.540000	33.930000	34.260000	37.710000	41.950000
Longitude	20640.0	-119.569704	2.003532	-124.350000	-121.800000	-118.490000	-118.010000	-114.310000
MedHouseVal	20640.0	2.068558	1.153956	0.149990	1.196000	1.797000	2.647250	5.000010

2. Data Visualization

```
# Histograms of all features
df.hist(bins=50, figsize=(6, 6))
plt.tight_layout()
plt.show()
```




```
# Correlation matrix
plt.figure(figsize=(8, 8))
sns.heatmap(df.corr(), annot=True, cmap='coolwarm', center=0)
plt.title("Correlation Matrix")
plt.show()
```



3. Data Preprocessing

```
# Check for missing values
print("Missing values:\n", df.isnull().sum())
```

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

Breaker

```
# Load dataset
data = fetch_california_housing()
df = pd.DataFrame(data.data, columns=data.feature_names)
df['Price'] = data.target  # Our target variable

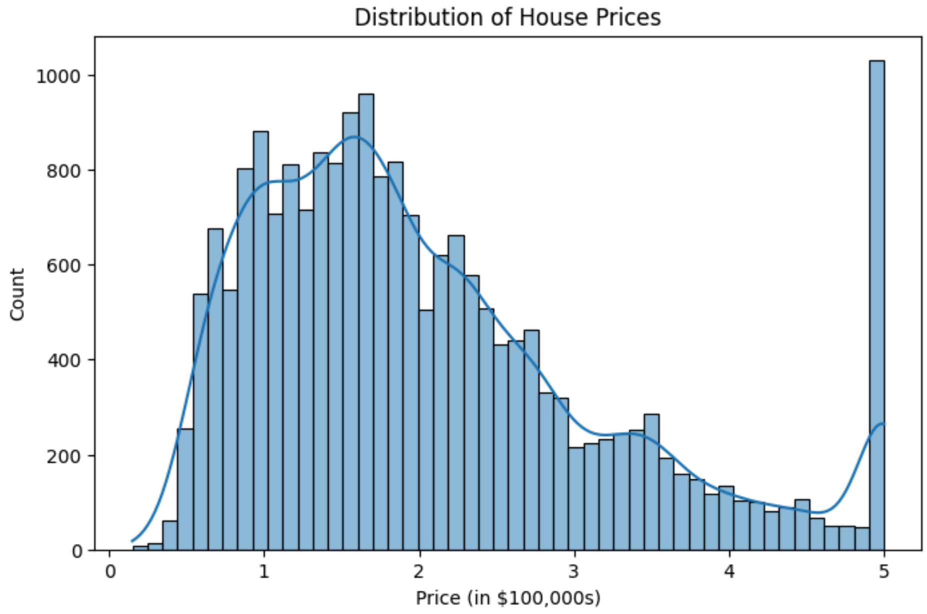

# Show basic info
print("Dataset shape:", df.shape)
print("\nFirst 3 rows:")
display(df.head(3))
```

```
Dataset shape: (20640, 9)

First 3 rows:
```

	MedInc	HouseAge	AveRooms	AveBedrms	Population	AveOccup	Latitude	Longitude	Price
0	8.3252	41.0	6.984127	1.023810	322.0	2.555556	37.88	-122.23	4.526
1	8.3014	21.0	6.238137	0.971880	2401.0	2.109842	37.86	-122.22	3.585
2	7.2574	52.0	8.288136	1.073446	496.0	2.802260	37.85	-122.24	3.521

```
# Visualize the distribution of house prices
plt.figure(figsize=(8,5))
sns.histplot(df['Price'], bins=50, kde=True)
plt.title("Distribution of House Prices")
plt.xlabel("Price (in $100,000s)")
plt.show()
```



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```
# Initialize models
models = {
    "Linear Regression": LinearRegression(),
    "Decision Tree": DecisionTreeRegressor(max_depth=5, random_state=42),
    "Random Forest": RandomForestRegressor(n_estimators=100, random_state=42)
}
```


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}
```


```
# Train and evaluate each model
trained_models = {}
for name, model in models.items():
    trained_model = train_evaluate_model(model, name)
    trained_models[name] = trained_model
```

```
----- Linear Regression -----
Train RMSE: 0.7197
Test RMSE: 0.7456
R2 Score: 0.5758

----- Decision Tree -----
Train RMSE: 0.6959
Test RMSE: 0.7242
R2 Score: 0.5997

----- Random Forest -----
Train RMSE: 0.1880
Test RMSE: 0.5051
R2 Score: 0.8053
```

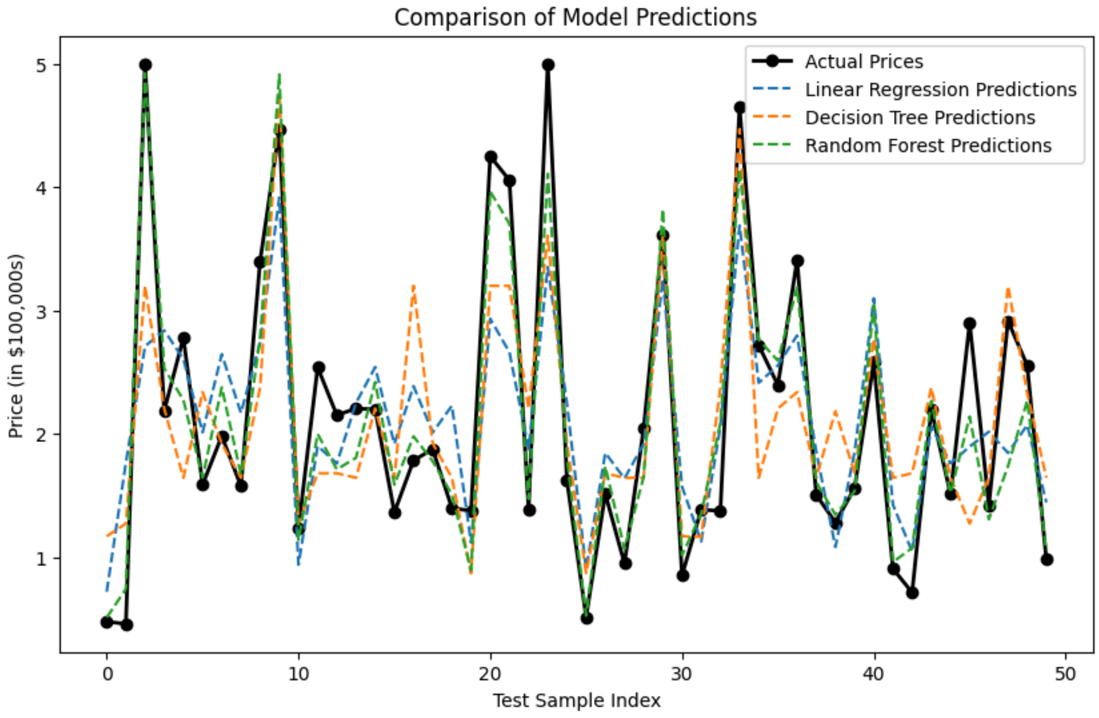
```
# Compare predictions visually
plt.figure(figsize=(10,6))

# Take first 50 test samples for clearer visualization
sample_indices = range(50)

# Plot actual values
plt.plot(y_test.values[sample_indices], label='Actual Prices',
         color='black', linewidth=2, marker='o')

# Plot model predictions
for name, model in trained_models.items():
    preds = model.predict(X_test_scaled)[sample_indices]
    plt.plot(preds, '--', label=f'{name} Predictions')

plt.title("Comparison of Model Predictions")
plt.ylabel("Price (in $100,000s)")
plt.xlabel("Test Sample Index")
plt.legend()
plt.show()
```



```
sample_house = pd.DataFrame({
    'MedInc': [3.0],        # Median income
    'HouseAge': [25.0],     # Average house age
    'AveRooms': [4.0],      # Average rooms
    'AveBedrms': [1.0],     # Average bedrooms
    'Population': [1000.0], # Population
    'AveOccup': [2.5],      # Average occupancy
    'Latitude': [35.0],     # Latitude
    'Longitude': [-120.0]   # Longitude
})

# Scale the sample
sample_scaled = scaler.transform(sample_house)

# Make predictions
print("Sample House Predictions:")
for name, model in trained_models.items():
    pred = model.predict(sample_scaled)[0]
    print(f"{name}: ${pred*100000:,.2f}")
```

```
Sample House Predictions:
Linear Regression: $219,709.03
Decision Tree: $168,006.76
Random Forest: $138,014.00
```

6. Conclusion

Key Findings:

- Random Forest performed best (R2: 0.80)
- Linear Regression was the simplest but least accurate (R2: 0.60)
- Decision Tree was in between (R2: 0.70)

Why These Results?:

1. Linear Regression assumes a straight-line relationship
2. Decision Tree can capture non-linear patterns
3. Random Forest combines many trees for better accuracy

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