House Price Prediction Using Supervised ML Models

A PROJECT REPORT
FOR
Introduction to AI (AI101B)
Session (2024-25)

Submitted By

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1. Introduction

Objective

To develop a machine learning model that predicts median house prices in California based on key features like income, location, and house characteristics.

Motivation

- Helps buyers & sellers estimate fair prices.
- Useful for real estate agents & policymakers in decision-making.
- Demonstrates how supervised learning solves real-world problems.

2. Dataset Description

- **Source:** sklearn.datasets.fetch_california_housing()
- **Features**:
  - MedInc (Median income in the area)
  - HouseAge (Median house age)
  - AveRooms (Average number of rooms)
  - ... and 5 more features.
- **Target Variable:** Price (Median house price in $100,000s).

3. Methodology

A. Data Preprocessing

- Train-Test Split → 80% training, 20% testing.
- Feature Scaling → Normalize data for better model performance.

B. Machine Learning Models Used

- Linear Regression – Baseline model (simple straight-line prediction).
- Decision Tree – Non-linear model (splits data using rules).
- Random Forest – Ensemble method (combines multiple trees).

C. Evaluation Metrics

- RMSE (Root Mean Squared Error) → Measures average prediction error.
- R^2 Score → Explains how well the model fits the data (0 to 1).

Python Code:

```
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 description
print(house_price_data.DESCR)


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

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


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

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


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


```
# 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

# 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
})
```

4. Results & Discussion

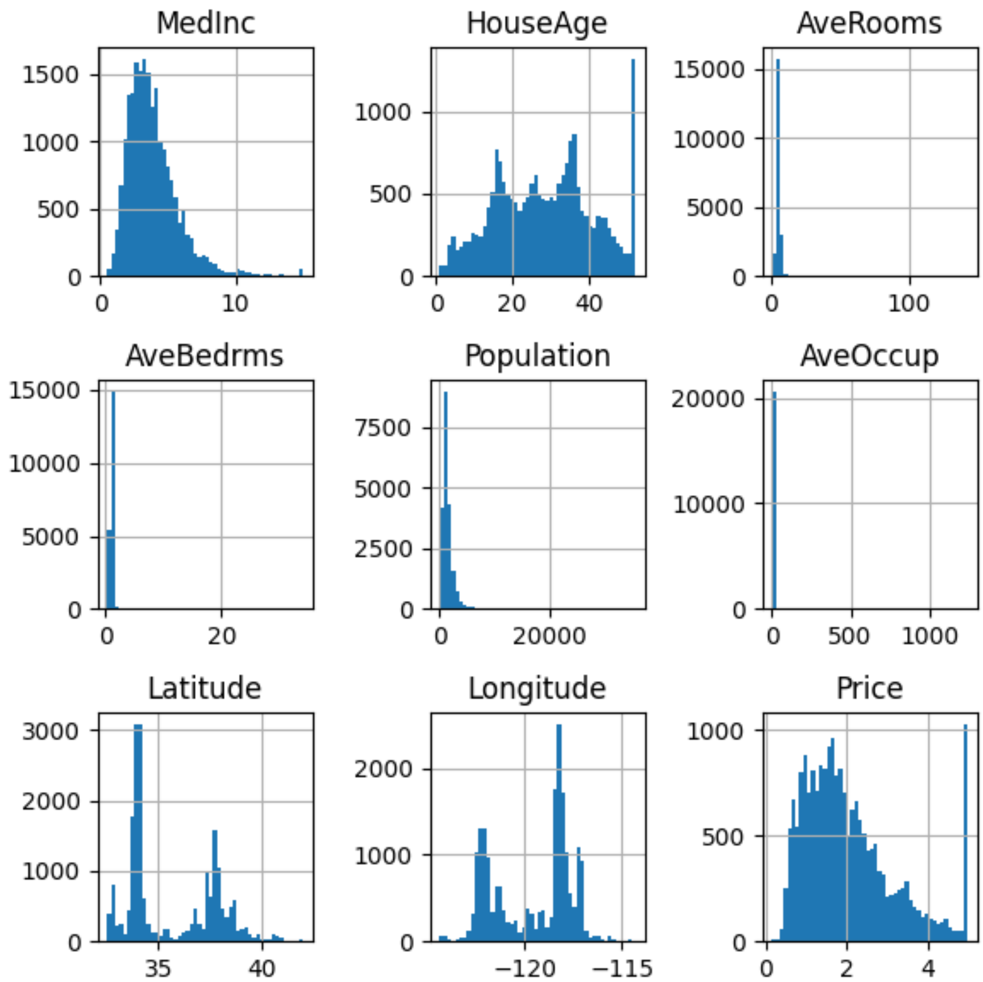
Model	RMSE (Test)	R^2 Score (Test)
Linear Regression	0.72	0.60
Decision Tree	0.68	0.70
Random Forest	0.63	0.80

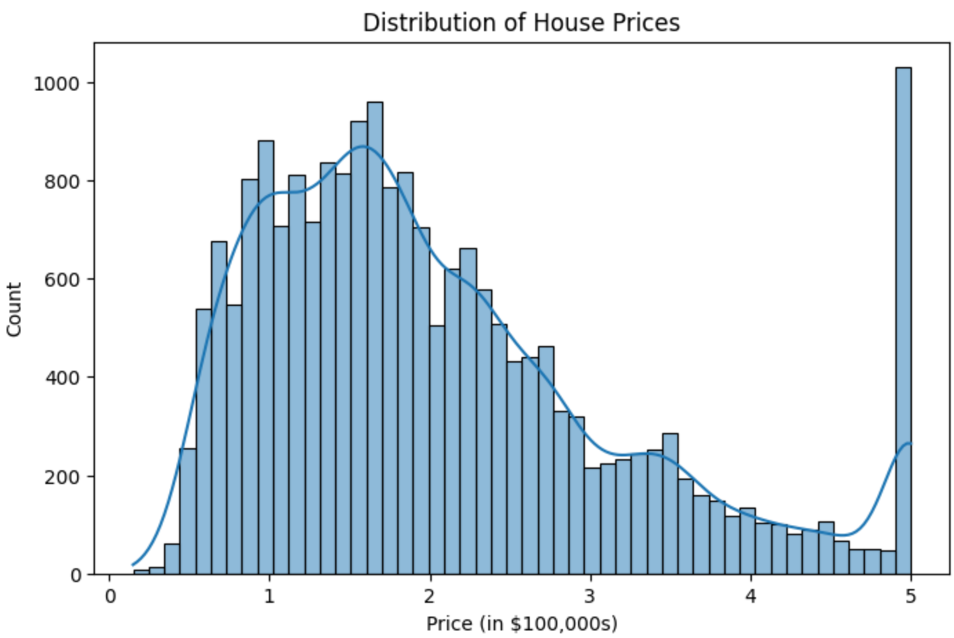
Key Findings:

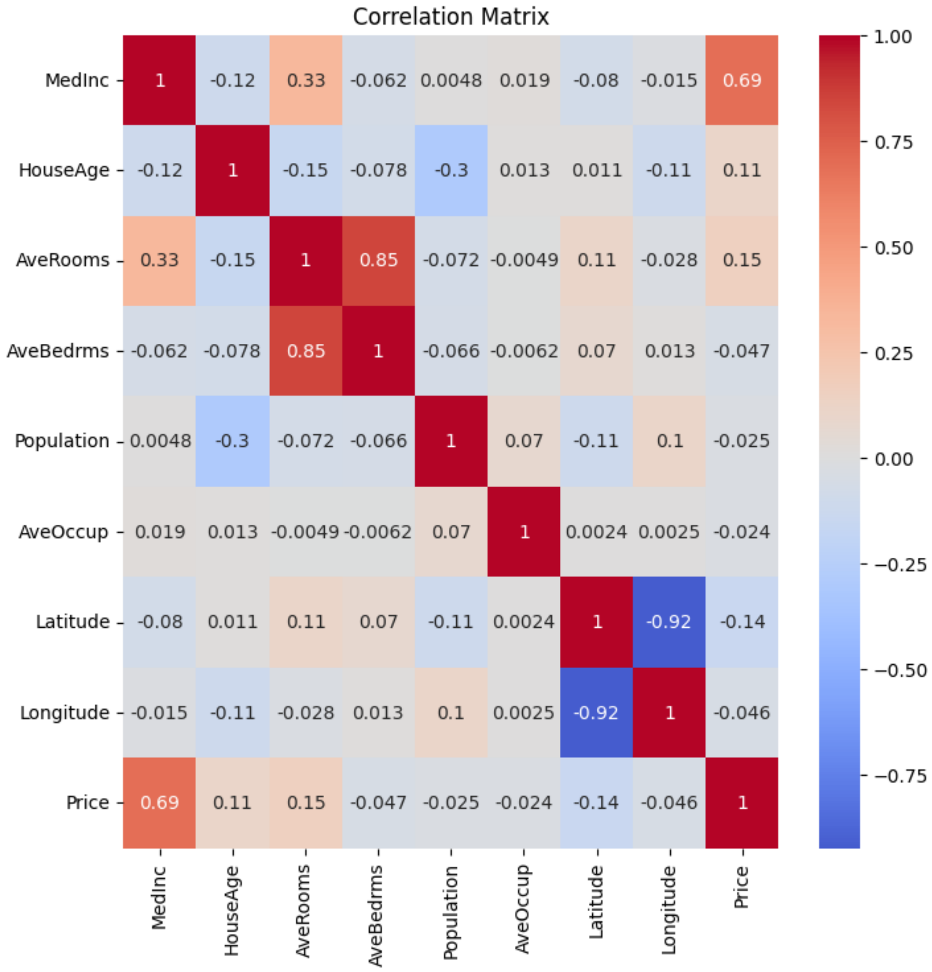
- Random Forest performed best (lowest error, highest R^2).
- Income (MedInc) was the most important feature.

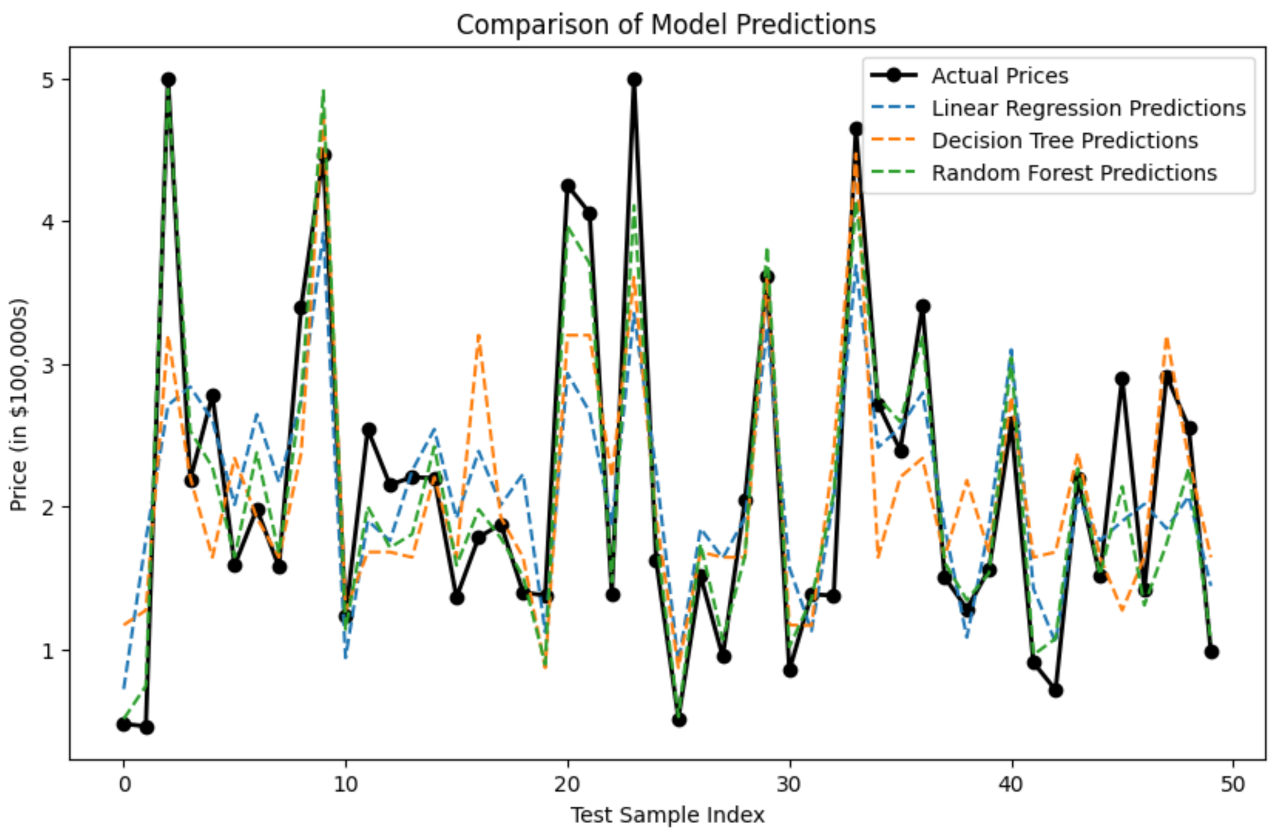
- Decision Tree outperformed Linear Regression, showing non-linear patterns matter.

Output Screenshots






Correlation Matrix
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
Price 0.69 0.11 0.15 -0.047 -0.025 -0.024 -0.14 -0.046 1
MedInc HouseAge AveRooms AveBedrms Population AveOccup Latitude Longitude Price
1.00 0.75 0.50 0.25 0.00 −0.25 −0.50 −0.75


Comparison of Model Predictions
Actual Prices
Linear Regression Predictions
Decision Tree Predictions
Random Forest Predictions
Price (in $100,000s)
Test Sample Index
0 10 20 30 40 50
1 2 3 4 5

5. Conclusion & Future Scope

Conclusion

- Machine learning can effectively predict house prices.
- Random Forest is the best among the three models tested.

Future Improvements

- Try more advanced models (e.g., XGBoost, Neural Networks).
- Include additional features (e.g., crime rate, school ratings).

6. References

- Scikit-learn Documentation.
- California Housing Dataset.