



**COLLEGE OF COMPUTING
DEPARTMENT OF SOFTWARE ENGINEERING
FUNDAMENTALS OF MACHINE LEARNING**

Individual Assignment

Name: Daniel Hailu

ID: 1401119

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Table of Contents

1. Overview
2. Dependencies
3. Data Preprocessing
4. Exploratory Data Analysis (EDA)
5. Feature Engineering
6. Model Training
7. Model Evaluation
8. Hyperparameter Tuning
9. Visualizations and Insights
10. Future Work & Conclusion

1. Overview

This project predicts house prices using **Random Forest Regression**. The dataset consists of **545 rows and 13 columns**, including numerical and categorical features like price, area, bedrooms, and furnishing status.

Objective:

- Develop an accurate model to predict house prices.
- Improve accuracy using feature engineering and data preprocessing.
- Evaluate the effectiveness of different modeling techniques.

2. Dependencies

Libraries Used:

- **numpy**: Numerical computations.
- **pandas**: Data manipulation.
- **matplotlib**, **seaborn**: Data visualization.
- **sklearn**: Machine learning model and preprocessing tools.
- **joblib**: Model serialization for saving trained models.

Dataset:

- **house-price.csv** containing features such as:
 - **Price**
 - **Area**
 - **Bedrooms, Bathrooms**
 - **Furnishing Status, Parking**
 - Other categorical features
-

3. Data Preprocessing

Steps:

1. **Load Data:** Read CSV into a DataFrame.
 2. **Check Missing Values:**
 - `df.isnull().sum()` shows no missing values.
 3. **Handle Outliers:**
 - Visualized using **boxplots**.
 - Removed extreme values using the **Interquartile Range (IQR) method**.
 4. **Encoding Categorical Variables:**
 - Used **OneHotEncoder** for categorical features.
 5. **Scaling Numerical Features:**
 - Applied **StandardScaler** for normalization.
 6. **Feature Engineering:**
 - Created new variables like **Price per sqft** to enhance prediction accuracy.
-

4. Exploratory Data Analysis (EDA)

Data Exploration:

- **Dataset Shape:** (545, 13)
- **Data Types:** Mixed numerical and categorical features.
- **Correlation Analysis:**
 - `sns.heatmap(df.corr())` to visualize correlations.

- Price highly correlated with Area and Bedrooms.

Key Insights:

- Bigger houses tend to be more expensive.
 - Categorical variables (e.g., `Furnishing Status`) influence pricing.
 - The dataset appears clean with no missing values.
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5. Feature Engineering

Feature engineering helps in improving the predictive power of the model by transforming raw data into meaningful features.

Added Features:

- **Price per Square Foot:** `df['price_per_sqft'] = df['price'] / df['area']`
- **Total Bathrooms:** Combining `bathrooms` and `additional_bathrooms` if applicable.
- **House Age:** Estimated based on available historical data.
- **Neighborhood Categorization:** Based on average pricing trends.

These features can provide additional insights and enhance model performance.

6. Model Training

Train-Test Split:

- Split data into 80% training, 20% testing using `train_test_split()`.

Preprocessing Pipeline:

- **Numerical Features:** Standardized with `StandardScaler()`.
- **Categorical Features:** Encoded using `OneHotEncoder()`.

Model Selection:

- **Random Forest Regressor** chosen due to its high accuracy and robustness.
- **Baseline Model:** Predicted average house price as a comparison.

Training:

- `model.fit(X_train, y_train)` to train Random Forest.

7. Model Evaluation

Performance Metrics:

- **Mean Absolute Error (MAE):** Measures average error.
- **Mean Squared Error (MSE):** Penalizes large errors.
- **R² Score:** Measures variance explained by the model.

The Random Forest model significantly outperforms the baseline.

8. Hyperparameter Tuning

Grid Search:

- Optimized hyperparameters like `n_estimators`, `max_depth`.
- Used `GridSearchCV` for tuning.

Best Parameters:

```
{'n_estimators': 200, 'max_depth': 20, 'min_samples_split': 5}
```

Tuning improved accuracy by reducing overfitting and optimizing model complexity.

9. Visualizations and Insights

Scatter Plot:

- **Price vs. Area:** Shows strong positive correlation.

Box Plots:

- **Categorical Variables vs. Price:** Shows pricing trends across categories.

Residual Analysis:

- Residuals randomly distributed → Model is well-fitted.

Feature Importance:

- **Random Forest provides feature importance metrics:**

```
importances = model.feature_importances_
```

- Area, Bedrooms, and Bathrooms were the most important features.

10. Future Work & Conclusion

Summary:

- Successfully built an accurate **Random Forest Regression Model**.
- Optimized hyperparameters improved performance.
- Model **outperformed the baseline**, proving its predictive ability.

Future Improvements:

- **Try alternative models like XGBoost and Gradient Boosting** for better results.
- **Collect more data** to enhance generalization.
- **Feature Selection Techniques:** Experiment with PCA and Recursive Feature Elimination.

The model shows strong predictive power, and further refinements can enhance performance.

Dataset Source: <https://www.tablab.app/csv/sample>

Thank You!