Forecasting House Prices Using Smart Regression Techniques

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1.Problem Statement

Accurate forecasting of house prices is crucial for stakeholders like real estate investors, buyers, and policy makers. This project aims to develop a predictive model using smart regression techniques, enabling highly accurate estimation of house prices based on various property, economic, and location features

2.Objectives of the Project

- Build a highly accurate model that predicts house prices.
- Understand which factors (like neighborhood, house size, etc.) impact prices the most.
- Create a simple tool that not only datascientists can use but, anyone can use to get predictions.

3.Scope of the Project

- We'll focus mainly on residential homes, not commercial properties.

- Start with data from one city or region, and later expand if needed.

- Use features like house size, number of bedrooms, proximity to schools, and local economic indicators.

- Try out different machine learning techniques — from simple Linear Regression to more advanced ones like Random Forests and XGBoost.

- We'll also build a clean, user-friendly dashboard where users can input house details and get a price prediction instantly.

4.Data Sources

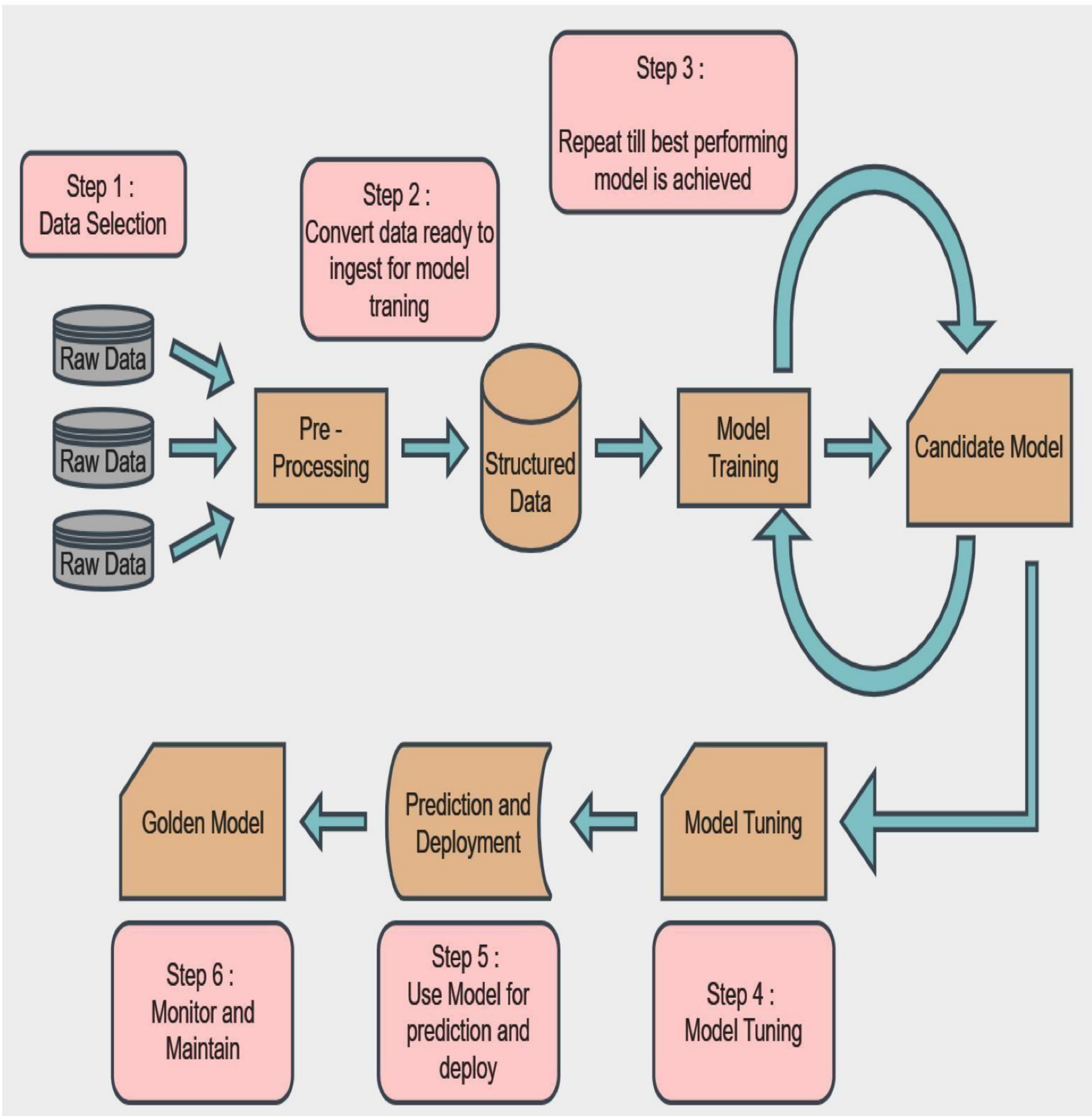
- Public datasets from places like Kaggle (example: the Ames Housing Dataset).

- Real estate listing sites (like Zillow or Realtor.com).

- Government and city property records (for verified historical data)

- Maybe even scrape a little data ourselves if needed — responsibly, of course!

Process Flowchart:



5.High-Level Methodology

Here's the big-picture plan:

1. Collect and prepare the data—clean it up, fill in missing values, and create new features that could help the model.
2. Explore the data — find patterns, outliers, and interesting relationships.
3. Build and test different models—see which regression techniques give us the best results.
4. Fine-tune the models—tweak the settings to squeeze out every bit of accuracy.
5. Deploy the best model—turn it into an dashboard so users can easily get house price estimates.

6.Tools and Technologies

- Programming Languages: Python
- Libraries/Frameworks: Scikit-learn, XGBoost, LightGBM, TensorFlow (optional for deep learning models)
- Data Visualization: Matplotlib, Seaborn, Plotly
- Data Processing: Pandas, NumPy

- Model Deployment: Flask/Django for web deployment, Streamlit for dashboards
- Version Control: Git and GitHub
- Environment: Jupyter Notebook, Google Colab, VS Code
- Cloud Platforms (optional for scalability): AWS, Azure

Code: import pandas as

pd import numpy as np

import seaborn as sns

import matplotlib.pyplot as

plt

from sklearn.model_selection import train_test_split, cross_val_score

from sklearn.preprocessing import StandardScaler from

sklearn.impute import SimpleImputer

from sklearn.linear_model import Ridge, Lasso, LinearRegression

from sklearn.ensemble import RandomForestRegressor from

sklearn.metrics import mean_squared_error import xgboost as xgb

import lightgbm as lgb

```
# Load the dataset (replace with actual path or use Kaggle dataset)
data = pd.read_csv('train.csv')


# Drop outliers (example) data =
data[data['GrLivArea'] < 4500]


# Target variable y
= data['SalePrice']
X = data.drop(['Id', 'SalePrice'], axis=1)


# 1. Data Preprocessing
# Identify numerical and categorical columns
num_cols = X.select_dtypes(include=['int64', 'float64']).columns
cat_cols = X.select_dtypes(include=['object']).columns


# Impute missing values
num_imputer = SimpleImputer(strategy='median') cat_imputer
= SimpleImputer(strategy='most_frequent')


X[num_cols] = num_imputer.fit_transform(X[num_cols])
X[cat_cols] = cat_imputer.fit_transform(X[cat_cols])
```

```
# One-hot encoding

X = pd.get_dummies(X, drop_first=True)


# Feature scaling scaler

= StandardScaler()

X_scaled = scaler.fit_transform(X)


# 2. Split the data

X_train, X_test, y_train, y_test = train_test_split(X_scaled, y,
test_size=0.2, random_state=42)


# 3. Define models models

= {

    'Linear Regression': LinearRegression(),

    'Lasso': Lasso(alpha=0.001),

    'Ridge': Ridge(alpha=10),

    'Random Forest': RandomForestRegressor(n_estimators=100),

    'XGBoost': xgb.XGBRegressor(),

    'LightGBM': lgb.LGBMRegressor()

}
```

```
# 4. Train and evaluate models results
= {} for name, model in
models.items():
model.fit(X_train, y_train)     preds =
model.predict(X_test)
    rmse = np.sqrt(mean_squared_error(y_test, preds))
results[name] = rmse     print(f"{name} RMSE:
{rmse:.2f}")


# 5. Visualize model performance plt.figure(figsize=(10,5))
sns.barplot(x=list(results.keys()), y=list(results.values()))
plt.ylabel("RMSE")
plt.title("Model Comparison - RMSE")
plt.xticks(rotation=45) plt.tight_layout()
plt.show()
```

7.Team Members and Roles

1.Yusuf shejin - Data Collection and Integration: Responsible for sourcing datasets, connecting APIs, and preparing the initial dataset for analysis.dk

2.Syed sharukh - Data Cleaning and EDA: Cleans andpreprocesses data, performs exploratory analysis, and generates initial insights.

3.Mohamed umar-Feature Engineering and Modeling: Workson feature extraction and selection; develops and trains machine learning models.

4.Tarik Ahamed - Evaluation and Optimization: Tuneshyperparameters, validates models, and documents performance metrics.

5.Mohamed danish - Documentation and Presentation: Compiles reports, prepares visualizations, and handles presentation and optional deployment.

6.Mohamed irfan- Data Visualization:

Matplotlib, Seaborn, Plotly.