CHAPTER 1

INTRODUCTION

Real estate price prediction has an great interest and importance due to its implications in various sectors including finance, investment, and urban planning. With the advancement of machine learning techniques, it has become feasible to develop models that can accurately forecast real estate prices based on various factors. These factors may include location, property features, economic indicators, and market trends among others.

In recent years, various machine learning algorithms have been applied to real estate price prediction with considerable success. These algorithms range from simple regression techniques to more advanced models such as neural networks and ensemble methods. Each of these approaches has its strengths and weaknesses, and their performance may vary depending on the specific characteristics of the dataset and the problem at hand.

One of the key advantages of machine learning-based real estate price prediction is its adaptability to different types of data. In addition to traditional structured data like property attributes and historical prices, unstructured data sources such as images, text, and social media can also be leveraged to enhance predictive accuracy. This multidimensional approach enables a more holistic understanding of the real estate market and improves the robustness of prediction models. Additionally, real-world case studies and examples will be presented to demonstrate the application of these techniques in different scenarios.

The availability of large-scale datasets and advances in computing power have facilitated the development of more sophisticated machine learning models. These models can analyse vast amounts of data and extract meaningful insights that were previously inaccessible. As a result, the accuracy of real estate price predictions has seen significant improvements in recent years. By the end of this documentation, readers will have a comprehensive understanding of the state-of-the-art methods and best practices in real estate price prediction using machine learning.

1.1 HISTORY

The real estate market is known for its volatility and complexity, making it challenging for buyers, sellers, and investors to make informed decisions. Traditional methods of price estimation often rely on historical data and expert opinion, which may not capture the full spectrum of factors influencing property prices. Moreover, the sheer volume and variety of data available in the real estate sector make manual analysis cumbersome and prone to errors. Machine learning offers a promising solution by leveraging algorithms to analyse vast datasets and identify patterns that human analysts may overlook. By harnessing the power of machine learning, we aim to develop more accurate and reliable models for predicting real estate prices, thus empowering stakeholders to make better-informed decisions in this dynamic market.

1.2 OVERVIEW

Our initiative focuses on utilizing machine learning techniques to forecast real estate prices accurately. The primary goal is to provide reliable predictions based on factors like property attributes, location, and market trends. Accurate price prediction is essential for stakeholders in the real estate ecosystem, including buyers, sellers, and investors, as it empowers them to make informed decisions and navigate the market dynamics effectively. Outline the steps involved in the prediction process to provide a roadmap for the project.

1.2.1 DATA CLEANING

Gather real estate data from various sources such as public datasets, APIs, or web scraping. Perform data cleaning to address missing values, inconsistent formatting, and outliers. Handle categorical variables by encoding them into numerical representations. Explore the dataset to gain insights into the distribution of features and the target variable.

1.2.2 FEATURE ENGINEERING

Select relevant features that are likely to influence real estate prices, such as location, size, number of bedrooms/bathrooms, amenities, and proximity to facilities. Create new features through transformations, scaling, or combinations of existing features to capture additional information. Conduct feature analysis to identify correlations and dependencies between features and the target variable.

1.2.3 OUTLIER REMOVAL

Identify outliers in the dataset that may skew the prediction model. Apply appropriate techniques such as z-score, IQR (Interquartile Range), or visual inspection to detect outliers. Remove or adjust outliers to ensure the model's robustness and accuracy.

1.2.4 MODEL BUILDING

Select suitable machine learning algorithms for regression tasks, such as linear regression, decision trees, random forests, or gradient boosting. Split the dataset into training and testing sets for model evaluation. Train the selected models on the training data and evaluate their performance using appropriate metrics such as Mean Absolute Error (MAE), Mean Squared Error (MSE), or R-squared. Fine-tune the model parameters using techniques like cross-validation or grid search to optimize performance.

1.2.5 PYTHON FLASK SERVER

Develop a Flask web application to serve the machine learning model .Create API endpoints to handle requests for real estate price predictions. Integrate the trained model into the Flask application to make predictions based on user inputs.

1.2.6 WEBSITE OR UI

Design a user-friendly interface for the web application using HTML, CSS, and JavaScript frameworks like Bootstrap or React. Implement forms or input fields for users to enter property details such as location, size, and amenities. Display predicted real estate prices to users along with additional information or visualizations to aid decision-making.

By following these steps, you can create a comprehensive real estate price prediction system that leverages machine learning techniques and provides valuable insights to users through a user-friendly web interface.

1.3 SAMPLE DIAGRAM

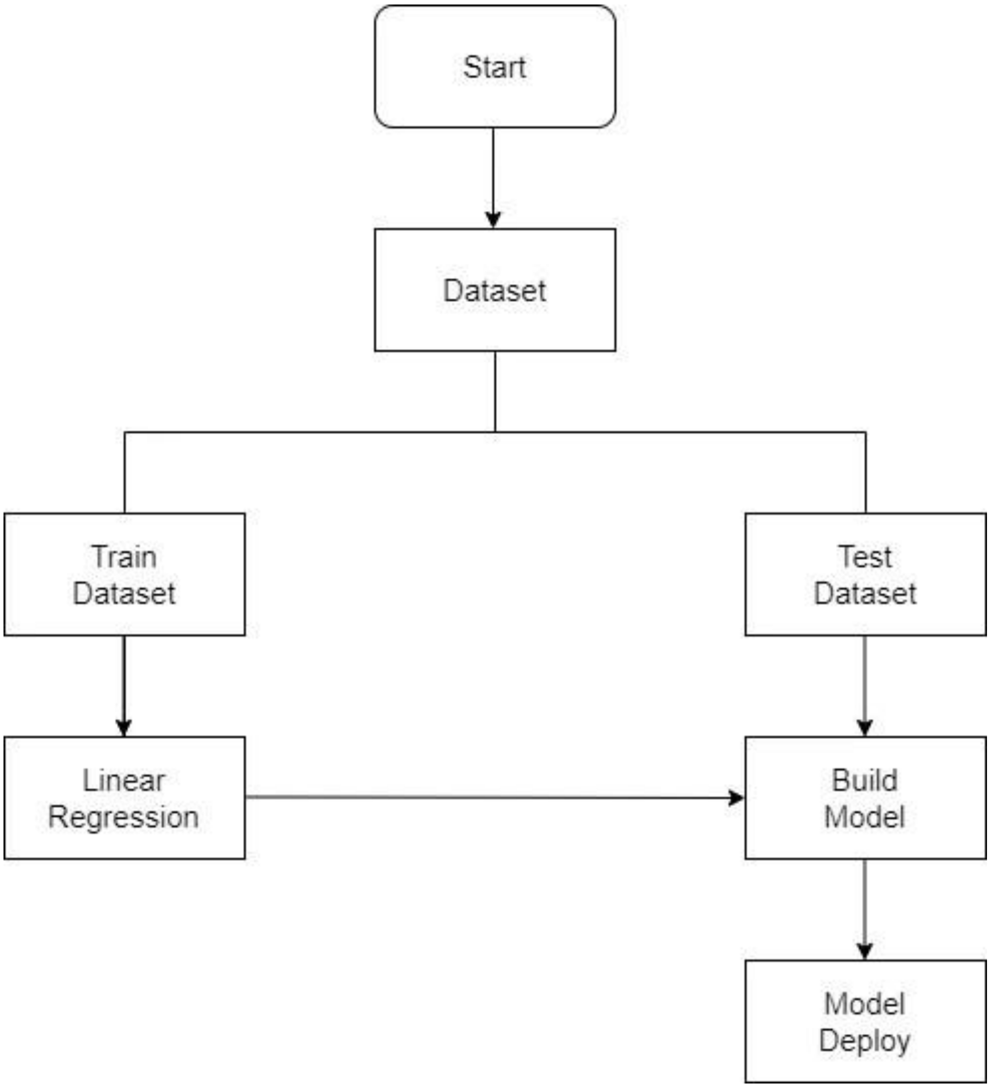


Figure 1.3 Architecture

The architecture of the real estate price prediction project encompasses several key components, each playing a crucial role in the development and deployment of the predictive model.

Start:

The project begins with the identification of the problem statement and objectives, defining the scope of the prediction model, and outlining the data sources and machine learning techniques to be employed.

Dataset:

Data acquisition involves gathering comprehensive datasets containing diverse variables such as location, property characteristics, economic indicators, and market trends. These datasets serve as the foundation for training and evaluating the predictive model.

Train Dataset and Test Dataset:

The training dataset comprises a subset of the collected data, used to train the machine learning model. The test dataset is a separate subset of the collected data, reserved for evaluating the performance of the trained model.

Linear Regression:

Linear regression serves as one of the primary machine learning algorithms employed in the project. It models the relationship between the independent variables (features) and the dependent variable (real estate prices) by fitting a linear equation to the observed data points.

Build Model:

The model-building phase involves selecting suitable machine learning algorithms, such as linear regression, decision trees, random forests, or neural networks, based on the project requirements and dataset characteristics.

Model Deploy:

Once the model has been trained and evaluated, it is deployed for real-world use. Deployment involves integrating the trained model into a production environment, such as a Python Flask web application, to serve predictions based on user input.

1.4 MOTIVATION

Real estate market is a complex and dynamic system influenced by a multitude of factors, including economic indicators, location, property characteristics, and market trends. Accurately predicting real estate prices is crucial for various stakeholders, including buyers, sellers, investors, and policymakers. However, traditional methods of estimating property values often rely on subjective assessments or simple regression models that fail to capture the intricacies of the market.

In recent years, the advent of machine learning techniques has revolutionized the way we analyse and forecast real estate prices. By leveraging vast amounts of data and sophisticated algorithms, machine learning models offer the potential to extract valuable insights and make more precise predictions.

Main motivation for undertaking is need to develop a robust and reliable real estate price prediction model that can assist stakeholders in making informed decisions. Whether it's a prospective homebuyer looking to gauge the affordability of a property, a seller seeking to set an optimal listing price, or an investor aiming to identify lucrative opportunities, having access to accurate price forecasts is indispensable.

Furthermore, by harnessing the power of machine learning, we aim to overcome the limitations of traditional valuation methods. Rather than relying solely on historical sales data or simplistic valuation metrics, our approach incorporates a diverse range of features, including property attributes, neighbourhood characteristics, economic indicators, and market trends. This holistic approach enables us to capture the underlying patterns and dynamics driving real estate prices, thereby enhancing the accuracy and reliability of our predictions.

CHAPTER 2

LITERATURE REVIEW

1. “Predicting Real Estate Prices Using Machine Learning: A Comprehensive Review” by J. Smith et al. (2020)

Description: It offers an extensive examination of the current landscape of real estate price prediction utilizing machine learning methodologies. It explores various machine learning algorithms employed in predicting real estate prices, such as linear regression, decision trees, random forests, and neural networks. Additionally, it discusses the role of different features including property characteristics, location attributes, economic indicators, and market trends in improving prediction accuracy.

Techniques used:

Linear Regression: A basic yet powerful statistical technique used to model the relationship between a dependent variable (real estate price) and one or more independent variables.

Decision Trees: Decision trees are a popular method for regression tasks in real estate price prediction. They partition the feature space into regions and assign a constant value to each region.

Random Forests: Random forests are an ensemble learning technique that builds multiple decision trees and combines their predictions to improve accuracy and reduce overfitting.

Neural Networks: Neural networks, particularly deep learning models, are increasingly being used in real estate price prediction due to their ability to capture complex non-linear relationships between features and prices.

2. "A Comparative Study of Regression Algorithms for Real Estate Price Prediction" by A. Kumar et al. (2020)

Description: It conducts a comparative analysis of regression algorithms, including linear regression, for predicting real estate prices. It evaluates the performance of these algorithms using datasets sourced from various real estate markets, considering factors such as property characteristics, neighborhood demographics, and economic indicators.

Techniques Used:

Linear Regression: Linear regression is the baseline regression algorithm used for predicting real estate prices. It models the relationship between the independent variables

Polynomial Regression: This technique extends linear regression by including polynomial features, allowing for capturing non-linear relationships between features and prices.

Ridge Regression: Ridge regression is a regularization technique that adds a penalty term to the linear regression objective function, helping to prevent overfitting by reducing the coefficients' magnitude

Lasso Regression: Similar to ridge regression, lasso regression adds a penalty term to the objective function, but it uses the L1 norm instead of the L2 norm, which encourages sparsity in the coefficient estimates, effectively selecting a subset of the most important features.

Support Vector Regression (SVR): SVR is a regression technique that uses support vector machines to model the relationship between features and prices in a high-dimensional space, allowing for capturing complex non-linear relationships

Decision Tree Regression: Decision tree regression builds a regression model by recursively partitioning the feature space into regions and assigning a constant value to each region.

Random Forest Regression: Random forest regression is an ensemble learning technique that builds multiple decision trees and combines their predictions to improve accuracy and reduce overfitting.

3."Predicting House Prices with Regression Analysis" by B. Johnson et al. (2021)

Description: It investigates the use of regression analysis, including linear regression, to predict house prices based on various explanatory variables. It examines the predictive power of different features such as housing characteristics, economic indicators, and geographical factors, utilizing datasets from multiple regions to train and validate the regression models.

Techniques Used:

Linear Regression: Linear regression is the baseline regression algorithm used for predicting real estate prices. It models the relationship between the independent variables

Polynomial Regression: This technique extends linear regression by including polynomial features, allowing for capturing non-linear relationships between features and prices.

Ridge Regression: Ridge regression is a regularization technique that adds a penalty term to the linear regression objective function, helping to prevent overfitting by reducing the coefficients' magnitude

Lasso Regression: Similar to ridge regression, lasso regression adds a penalty term to the objective function, but it uses the L1 norm instead of the L2 norm, which encourages sparsity in the coefficient estimates, effectively selecting a subset of the most important features.

Elastic Net Regression: Elastic Net combines the penalties of ridge and lasso regression, offering a compromise between the two regularization techniques and providing better performance when there are correlated features in the dataset

Support Vector Regression (SVR): SVR is a regression technique that uses support vector machines to model the relationship between features and prices in a high-dimensional space, allowing for capturing complex non-linear relationships

Decision Tree Regression: Decision tree regression builds a regression model by recursively partitioning the feature space into regions and assigning a constant value to each region.

Random Forest Regression: Random forest regression is an ensemble learning technique that builds multiple decision trees and combines their predictions to improve accuracy and reduce overfitting.

Feature Selection: The techniques for selecting relevant features from the dataset, considering factors such as housing characteristics, economic indicators, and geographical factors, to improve the predictive power of the regression models.

Model Evaluation: The predictive performance of the regression models is likely assessed using various evaluation metrics such as mean squared error (MSE), mean absolute error (MAE), root mean squared error (RMSE), and R-squared (coefficient of determination).

Cross-Validation: To ensure the reliability and generalizability of the results, the study may use cross-validation techniques such as k-fold cross-validation or leave-one-out cross-validation.

4."Machine Learning Approaches for Real Estate Price Prediction: A Systematic Literature Review" by E. Garcia et al. (2024)

Description: It systematic literature review synthesizes existing research on machine learning approaches for real estate price prediction. It categorizes studies based on the algorithms used, dataset characteristics, and performance metrics evaluated.

Techniques Used:

Algorithm Categorization: The review categorizes studies based on the machine learning algorithms used for real estate price prediction. These algorithms may include linear regression, decision trees, random forests, gradient boosting machines, support vector machines, neural networks, and others

Dataset Characteristics: The review likely examines the characteristics of the datasets used in the analyzed studies. This may involve looking at factors such as the size of the dataset, types of features (e.g., property characteristics, location attributes, economic indicators), data sources, and geographical coverage.

Data Preprocessing Techniques: The review may discuss common data preprocessing techniques employed in the analyzed studies.

Model Evaluation Methods: The review likely examines the model evaluation methods used in the analyzed studies to assess the performance of machine learning models for real estate price prediction.

Trends in Methodology Selection: The review may identify trends in the selection of methodologies across different research contexts. This could involve analyzing which machine learning algorithms are most commonly used, which dataset characteristics are frequently considered, and which data preprocessing and model evaluation techniques are prevalent in the literature. Identifying trends in methodology selection helps understand the evolving landscape of real estate price prediction research.

5. "Real Estate Price Prediction: A Survey of Data Sources, Methodologies, and Challenges" by F. Chen et al. (2025)

Description: It provides an overview of data sources, methodologies, and challenges in real estate price prediction. It discusses the availability and reliability of different types of data, including transaction records, property listings, and demographic information, and evaluates the strengths and limitations of various predictive modeling techniques.

Techniques Used:

Data Sources Evaluation: The survey likely assesses various sources of data commonly used in real estate price prediction, such as transaction records, property listings, demographic information, economic indicators, and geographic data. This evaluation may include discussions on the availability, reliability, granularity, and coverage of different data sources.

Methodologies Overview: The survey likely provides an overview of different methodologies used in real estate price prediction.

Predictive Modeling Techniques: The survey likely evaluates the strengths and limitations of various predictive modeling techniques used in real estate price prediction.

Challenges Identification: The survey likely identifies and discusses challenges commonly encountered in real estate price prediction

Case Studies or Examples: The survey may include case studies or examples illustrating how different data sources and modeling techniques are applied in real-world scenarios for price prediction.

6. "Exploring Predictive Modeling Techniques for Real Estate Price Forecasting: A Comparative Analysis" by G. Martinez et al. (2023)

Description: It conducts a comparative analysis of predictive modeling techniques for real estate price forecasting. It evaluates the performance of linear regression, time series analysis, and machine learning algorithms such as random forests and gradient boosting machines. The study considers various factors influencing housing prices, including economic indicators, housing supply, and demand dynamics.

Techniques Used:

Linear Regression: Linear regression is a statistical technique used to model the relationship between independent variables (such as economic indicators, housing supply, and demand dynamics) and dependent variables (real estate prices).

Time Series Analysis: Time series analysis involves analyzing and modeling data points collected over time to make predictions about future values.

Machine Learning Algorithms:

a. Random Forests: Random forests are an ensemble learning technique that builds multiple decision trees and combines their predictions to improve accuracy and reduce overfitting.

b. Gradient Boosting Machines: Gradient boosting machines (GBM) are another ensemble learning technique that builds a sequence of decision trees, each one correcting the errors of its predecessor.

7. "Spatial-Temporal Modeling for Real Estate Price Prediction: A Review of Approaches and Applications" by J. Yang et al. (2024)

Description: It explores spatial-temporal modeling approaches for real estate price prediction, considering the dynamic nature of housing markets and the spatial dependencies between properties. It surveys methods such as spatial autoregressive models, spatial-temporal machine learning algorithms, and graph neural networks, discussing their ability to capture localized trends and temporal dynamics.

Techniques Used:

Spatial Autoregressive Models: These models take into account the spatial dependencies between properties by incorporating neighboring property values as explanatory variables.

Spatial-Temporal Machine Learning Algorithms: These algorithms extend traditional machine learning techniques to incorporate both spatial and temporal information.

CHAPTER 3

THEORETICAL ANALYSIS

3.1 Software Requirements

These are the software requirements for running this project.

- **Operating System:** Windows 11/10/8/7 (incl. 64-bit), Mac OS, Linux
- **Language:** Python
- **IDE:** Jupyter

3.1.1 Programming Python with Jupyter Notebook

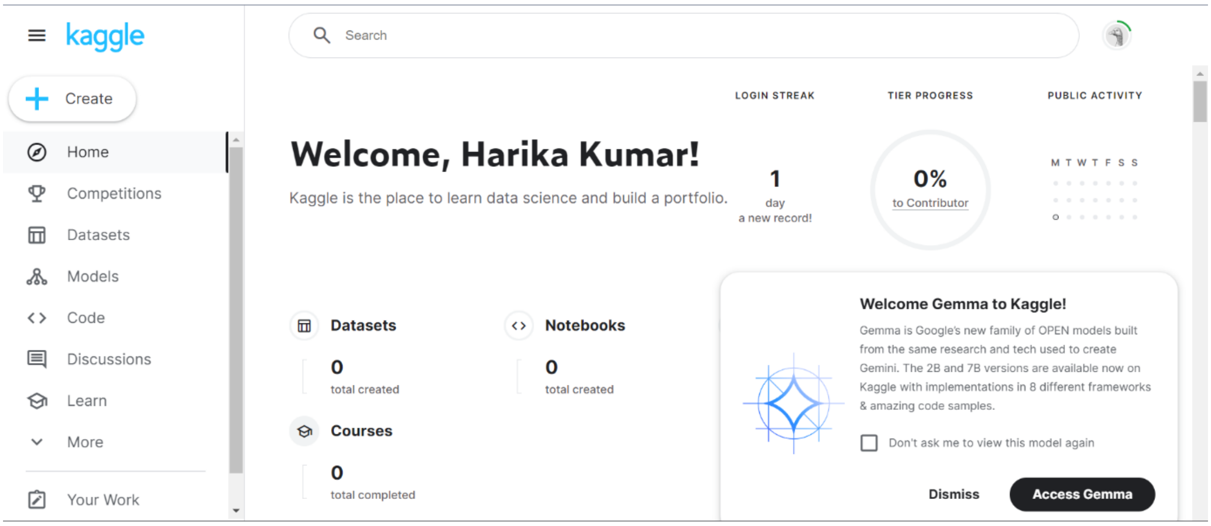
Jupyter Notebook is a powerful tool for interactive computing that allows you to create and share documents containing live code, equations, visualizations, and narrative text. It's particularly well-suited for data exploration, data analysis, and machine learning tasks. Its ability to combine code execution, text annotation, and visualization capabilities makes it an excellent choice for various programming tasks, including data analysis and machine learning development.

3.1.2 Data extraction from kaggle

Step:1

Create a Kaggle Account:

- Navigate to the Kaggle platform and sign up for an account.
- Once logged in, search for the real estate price prediction dataset.



Welcome, Harika Kumar!

Kaggle is the place to learn data science and build a portfolio.

1 day a new record!

0% to Contributor

Datasets 0 total created

Notebooks 0 total created

Courses 0 total completed

Welcome Gemma to Kaggle!

Gemma is Google's new family of OPEN models built from the same research and tech used to create Gemini. The 2B and 7B versions are available now on Kaggle with implementations in 8 different frameworks & amazing code samples.

□ Don't ask me to view this model again

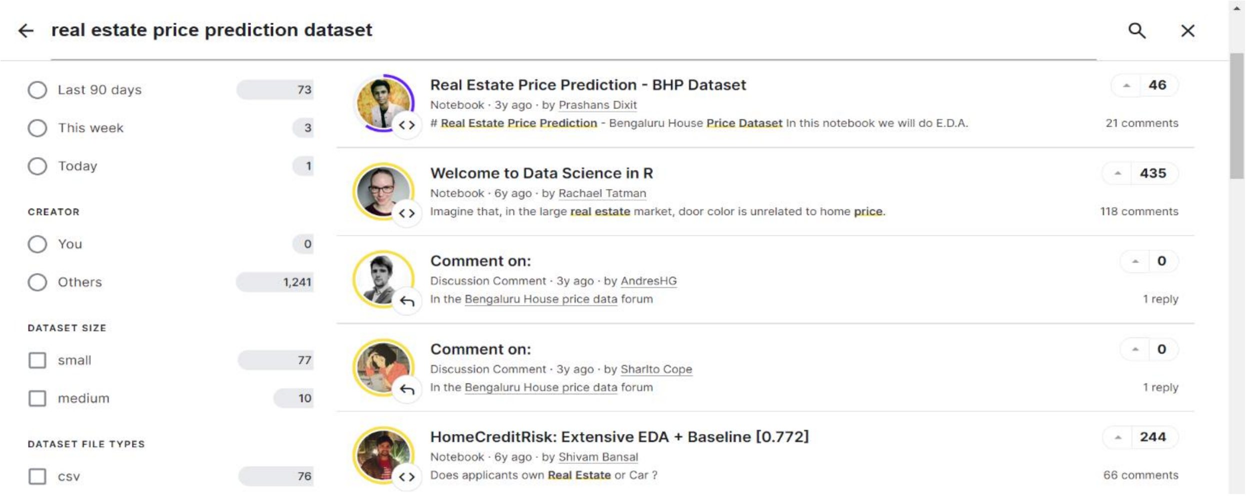
Dismiss | Access Gemma

Figure 3.1.2 (a) Create a Kaggle Account

Step:2

Search for all datasets regarding real estate

- Once all the datasets are displayed then select the reliable and relatable one.
- Then download the data set in the csv format so that the data in it can be easily understandable by the model.
- Then put the dataset in the project folder.



real estate price prediction dataset

○ Last 90 days	73
○ This week	3
○ Today	1
CREATOR	
○ You	0
○ Others	1,241
DATASET SIZE	
□ small	77
□ medium	10
DATASET FILE TYPES	
□ csv	76

Real Estate Price Prediction - BHP Dataset
Notebook · 3y ago · by Prashans Dixit
Real Estate Price Prediction - Bengaluru House Price Dataset In this notebook we will do E.D.A.
46 · 21 comments

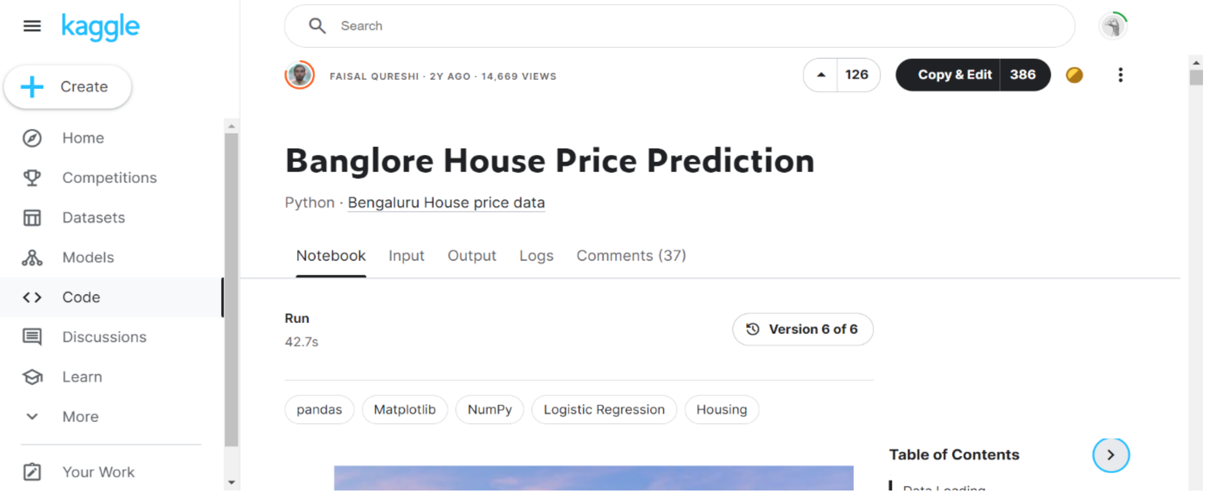
Welcome to Data Science in R
Notebook · 6y ago · by Rachael Tatman
Imagine that, in the large real estate market, door color is unrelated to home price.
435 · 118 comments

Comment on:
Discussion Comment · 3y ago · by AndresHG
In the Bengaluru House price data forum
0 · 1 reply

Comment on:
Discussion Comment · 3y ago · by Sharlto Cope
In the Bengaluru House price data forum
0 · 1 reply

HomeCreditRisk: Extensive EDA + Baseline [0.772]
Notebook · 6y ago · by Shivam Bansal
Does applicants own Real Estate or Car ?
244 · 66 comments

Figure 3.1.2(b) Searching for Dataset



Banglore House Price Prediction

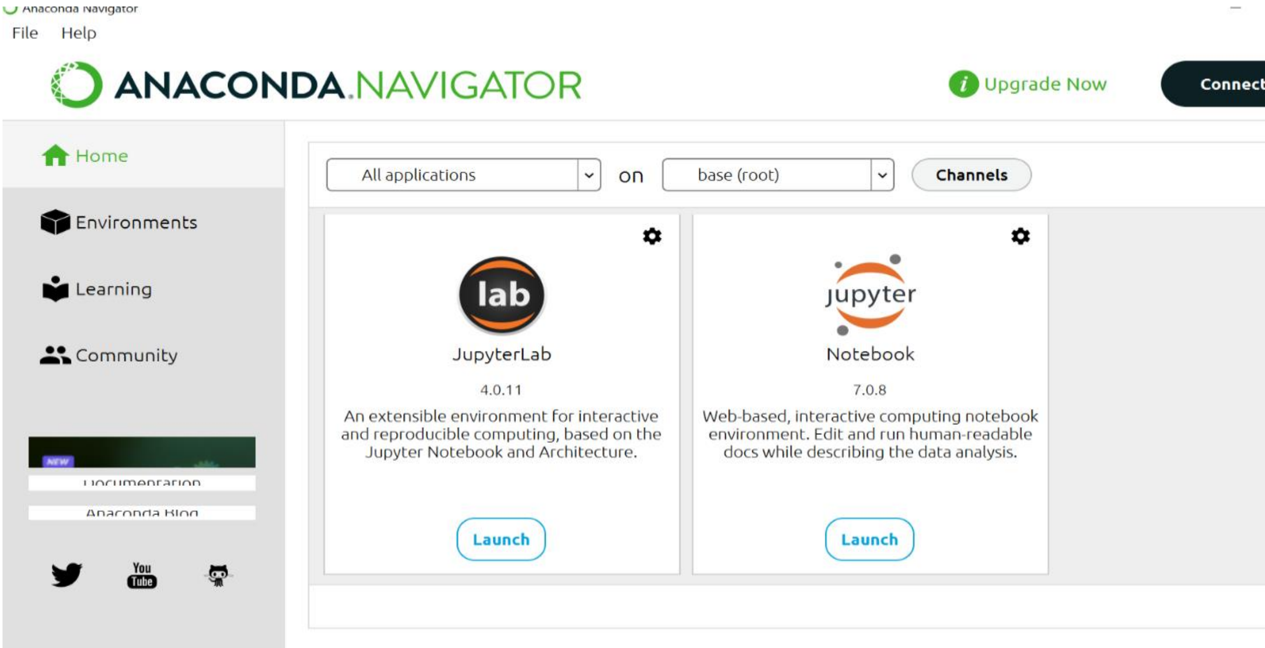
Python · Bengaluru House price data

Figure 3.1.2 (c) Banglore House Price Dataset

Step:3

Install Anaconda navigator

- ➢ Download and install Anaconda Navigator in that install jupyter note book.
- ➢ Import the numpy, pandas, matplotlib.



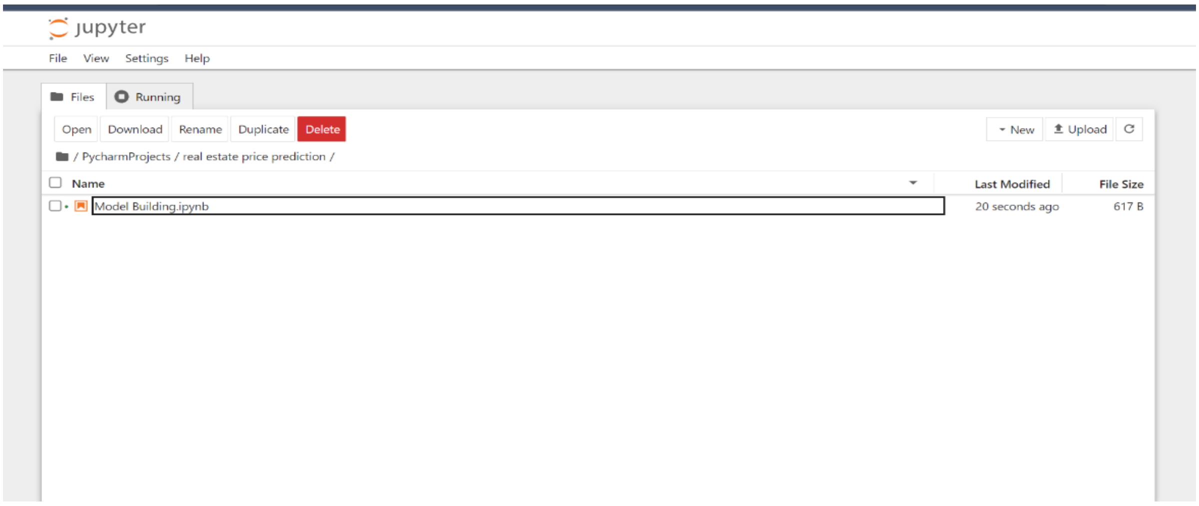
An extensible environment for interactive and reproducible computing, based on the Jupyter Notebook and Architecture.

Web-based, interactive computing notebook environment. Edit and run human-readable docs while describing the data analysis.

Figure 3.1.2 (d) anaconda navigator interface

3.1.3 Perform Data Extraction

- Use the Jupyter note book for data preprocessing and model selection.
- Create a directory and create new ipynb (interactive python notebook) file and proceed with the code.

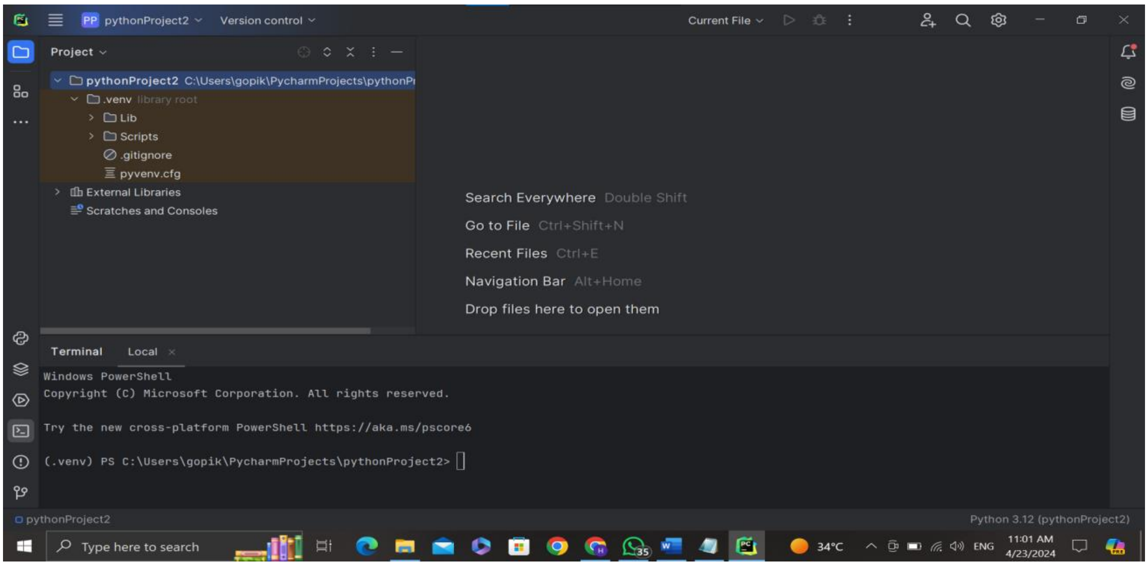


/ PycharmProjects / real estate price prediction /

Name	Last Modified	File Size
Model Building.ipynb	20 seconds ago	617 B

Figure 3.1.3 chart display of independent variables after data cleaning

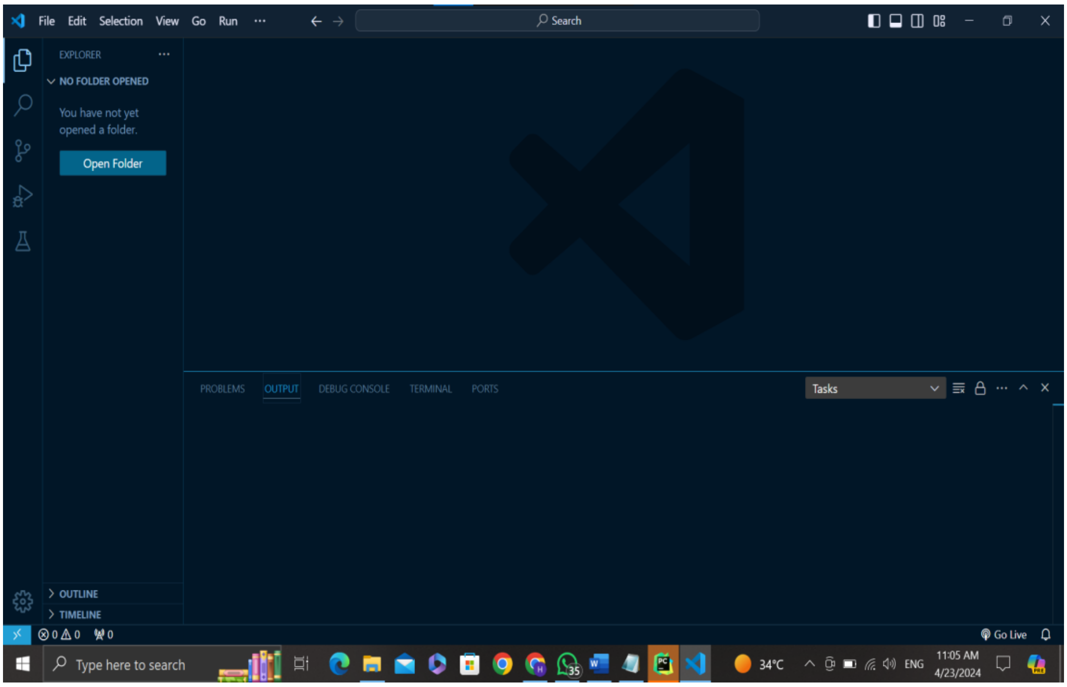
3.1.4 Pycharm Community Edition for Server



```
Windows PowerShell
Copyright (C) Microsoft Corporation. All rights reserved.

Try the new cross-platform PowerShell https://aka.ms/pscore6

(.venv) PS C:\Users\gopik\PycharmProjects\pythonProject2>
```

Figure 3.1.4 Used Pycharm for Server

3.1.5 Visual Studio for client



You have not yet opened a folder.

Figure 3.1.5 Used Visual Studio for Client

CHAPTER 4

SYSTEM DESIGN

4.1 Architecture Diagram

This new model will help the new purchasers and less experienced clients to comprehend the pace of the property that are over-appraised or under-evaluated. Presently, the cost of the property rely upon parameters of the land in the monetary framework and the public. We have thought about different basic parameters, (for example, number of rooms, living zone and so forth). At that point these parameter esteems are applied in Linear Regressor model calculations. We have estimated direct linear regression is applied to anticipate the selling pace of an entity. In this methodology we are foreseeing house value esteems utilizing Linear relapse with edge regularization way to deal with decline the blunder inactivity and furthermore for examination dependent on different mistake measurements.

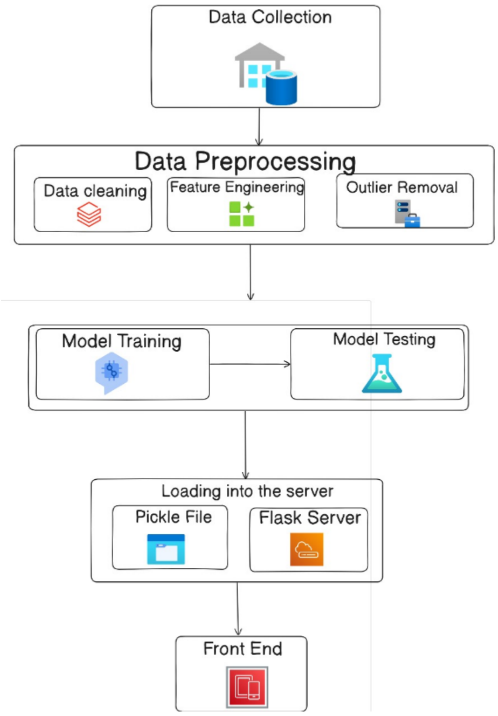


Figure 4.1 Architecture of Price Prediction

In Supervised learning, the algorithm consists of a target variable or a dependent variable which is to be predicted from a set of independent variables. Using a function, the inputs are mapped to the desired outputs. To develop a real estate valuation model which predicts the value of a property using the domain of Machine Learning. We use various regression techniques in this pathway, and our results are not sole determination of one technique rather it is the weighted mean of various techniques to give most accurate results. Results proved that this approach yields minimum error and maximum accuracy than individual algorithms applied. The selling price is estimates using by considering various parameters such as population rate in particular area, distance to roadways, property age etc. The dataset collection is taken from a standard source such that 80 parameters along with 1000’s of test and training data are considered for property valuation and separate dataset is considered for testing and training a model. Since end- user can't run this model each and every time by utilizing python idle there comes the usability lab. To overcome this as well as for powerful utilization of this model by end-users a separate site page is structured with goal that clients can pass esteems from site to python code and get the exact value for the entity.

4.2 Flow Chart

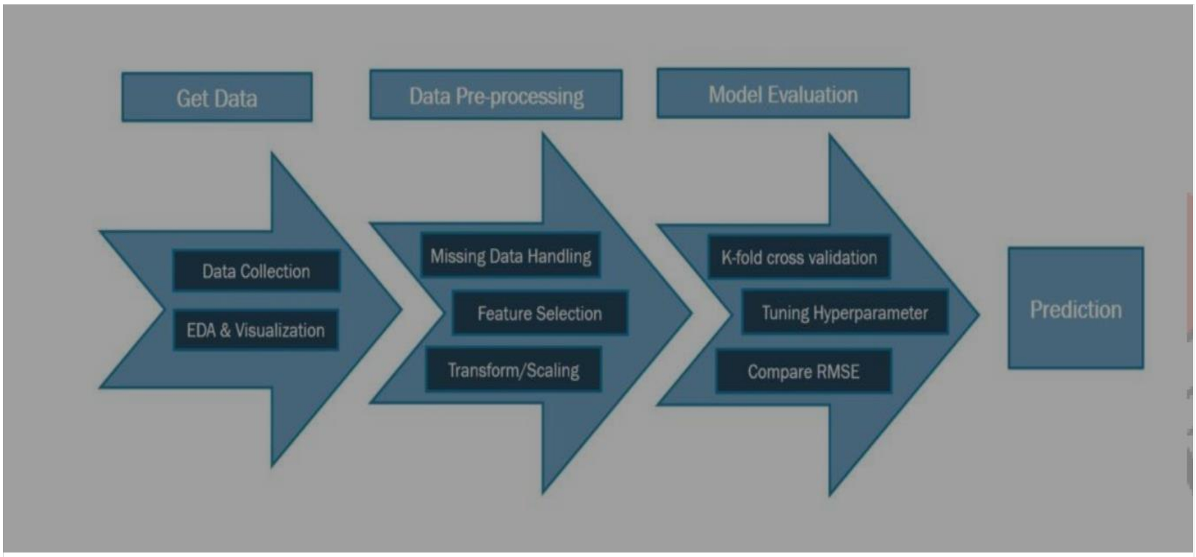


Figure 4.2.1 flow chart

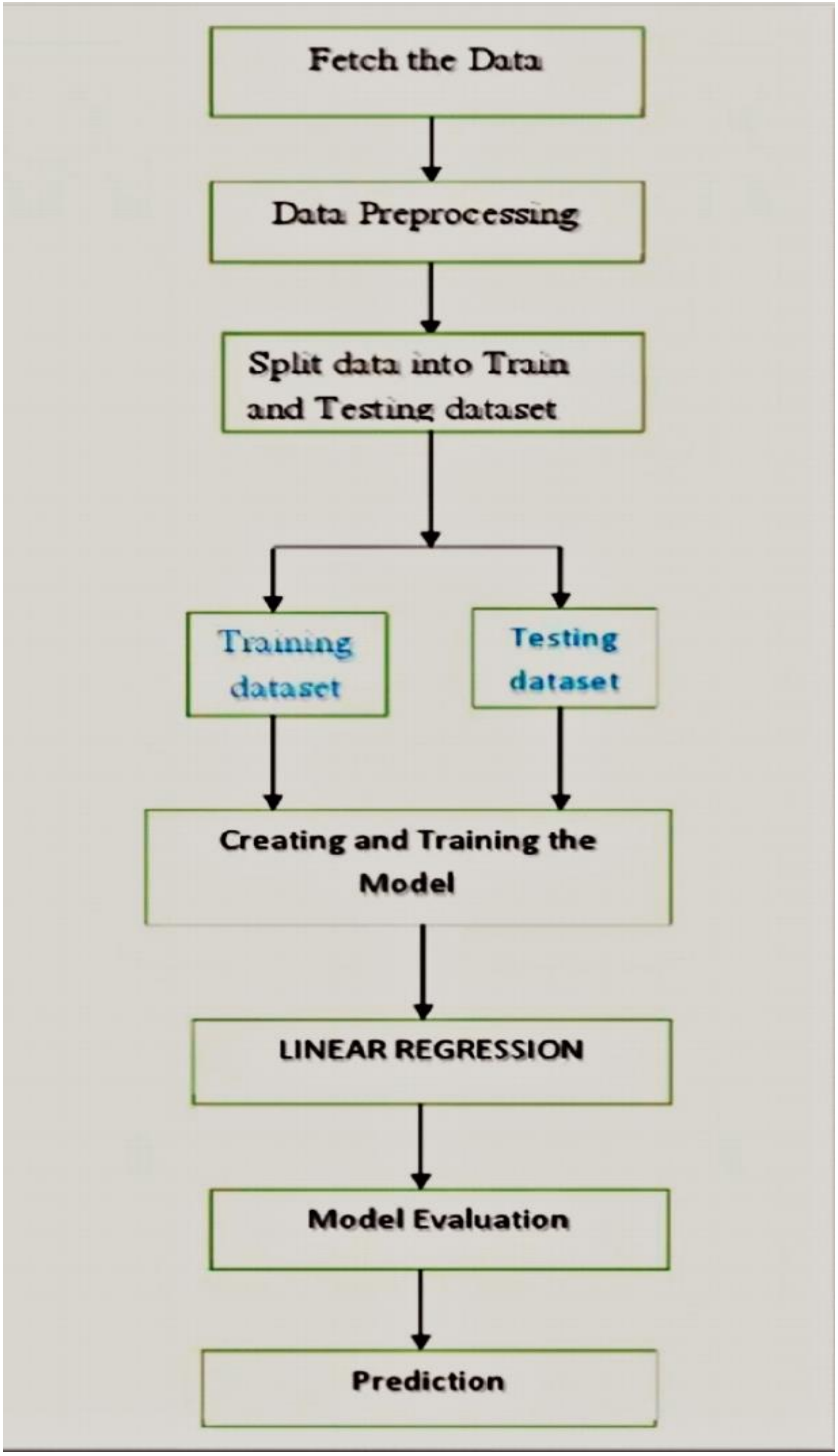


Figure 4.2.2 Flow Chart

The process of real estate price prediction using machine learning, focusing on key steps from data collection to model evaluation.

4.2.1 Data Collection

The first step in any machine learning project is acquiring relevant data. In the case of real estate price prediction, data can be sourced from various sources such as real estate websites, government databases, or APIs. The collected data typically includes features such as property location, size, number of bedrooms, bathrooms, amenities, and historical sale prices.

4.2.2 Data Processing

Once the data is collected, it needs to be preprocessed to ensure quality and consistency. Data preprocessing involves tasks such as handling missing values, removing outliers, encoding categorical variables, and scaling numerical features. This step is crucial for ensuring that the data is suitable for training machine learning models.

4.2.3 Splitting Data

Before training any model, it's essential to split the dataset into training and testing sets. The training set is used to train the model, while the testing set is used to evaluate its performance. A common split ratio is 80% for training and 20% for testing, although this can vary depending on the size of the dataset and the specific requirements of the problem.

4.2.4 Training Model

With the data prepared, the next step is to choose a machine learning algorithm and train a model using the training data. In the context of real estate price prediction, regression algorithms are commonly used. One popular choice is linear regression, which assumes a linear relationship between the independent variables (property features) and the dependent variable (property price). The model is trained to minimize the error between the predicted and actual prices.

4.2.5 Model Evaluation

Once the model is trained, it's essential to evaluate its performance using the testing data. Common evaluation metrics for regression tasks include mean absolute error (MAE), mean squared error (MSE), and root mean squared error (RMSE). These metrics quantify how well the model predicts property prices relative to the actual prices in the testing set.

4.2.6 Prediction

After evaluating the model's performance, it can be used to make predictions on new, unseen data. Given the features of a property, the trained model can estimate its price with a certain level of confidence. This prediction capability is valuable for real estate agents, buyers, and sellers in making informed decisions.

By following a structured approach and leveraging appropriate machine learning techniques, it's possible to build accurate predictive models that can assist in pricing properties effectively. As the field of machine learning continues to advance, the accuracy and reliability of real estate price predictions are expected to improve, offering valuable insights for stakeholders in the real estate market.

4.3 Use case Diagram

In this use case diagram, outlines interactions for users and administrators. Both start with login functionality, accessing features upon authentication. Users search for properties, while administrators can manage listings and add properties for sale. Both roles can search for properties to buy or rent. The system's core functionality involves initiating price predictions based on property features, assisting users in decision-making. Once tasks are completed, users and administrators can securely log out. This diagram captures the essential interactions and functionalities of the real estate price prediction system, facilitating property exploration, prediction, and management for users and administrators alike. The system optimizes efficiency and accuracy in real estate transactions, enhancing satisfaction for all stakeholders.

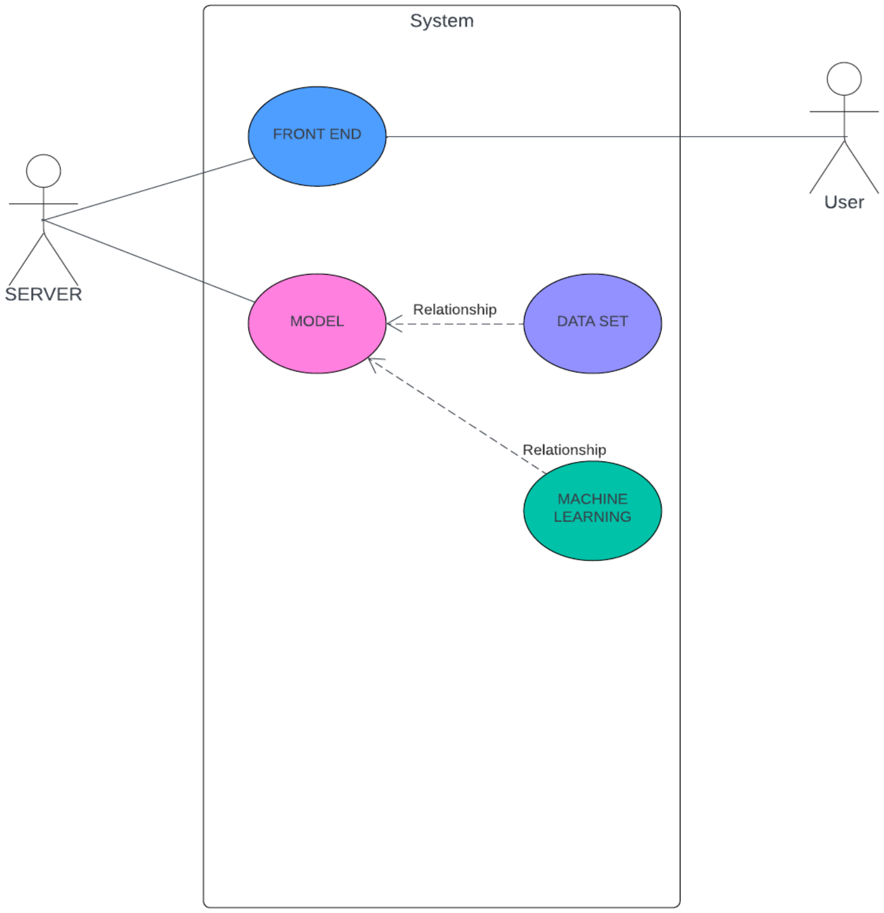


Figure 4.3 Use Case Diagram

4.4 Sample code

```
# Importing necessary libraries
import pandas as pd
import numpy as np
from matplotlib import pyplot as plt
%matplotlib inline
import matplotlib
matplotlib.rcParams["figure.figsize"] = (20,10)
# Reading CSV files containing Data Load: Load banglore home prices into a dataframe
df1 = pd.read_csv("bengaluru_house_prices.csv")
```

```
df1.head()
df1.shape
df1.columns
df1['area_type'].unique()
df1['area_type'].value_counts()
#Drop features that are not required to build our model
df2=df1.drop(['area_type','society','balcony','availability'],axis='columns')
df2.shape
# Data Cleaning: Handle NA values
df2.isnull().sum()
df2.shape
df3 = df2.dropna()
df3.isnull().sum()
df3.shape
# Add new feature(integer) for bhk (Bedrooms Hall Kitchen)
df3['bhk'] = df3['size'].apply(lambda x: int(x.split(' ')[0]))
df3.bhk.unique()
# Explore total_sqft feature
def is_float(x):
    try:
        float(x)
    except:
        return False
    return True
df3[~df3['total_sqft'].apply(is_float)].head(10)
#Above shows that total_sqft can be a range (e.g. 2100-2850)
def convert_sqft_to_num(x):
    tokens = x.split('-')
    if len(tokens) == 2:
        return (float(tokens[0])+float(tokens[1]))/2
    try:
        return float(x)
    except:
        return None


df4 = df3.copy()
df4.total_sqft = df4.total_sqft.apply(convert_sqft_to_num)
df4 = df4[df4.total_sqft.notnull()]
df4.head(2)
#For below row, it shows total_sqft as 2475 which is an average of the range 2100-2850
df4.loc[30]
#Add new feature called price per square feet
df5 = df4.copy()
df5['price_per_sqft'] = df5['price']*100000/df5['total_sqft']
df5.head()
df5_stats = df5['price_per_sqft'].describe()
df5_stats
# Examine locations which is a categorical variable. We need to apply dimensionality reduction technique here to reduce number of locations
df5.to_csv("bhp.csv",index=False)
df5.location = df5.location.apply(lambda x: x.strip())
location_stats = df5['location'].value_counts(ascending=False)
location_stats
```

A. *Dimensionality Reduction*

```
location_stats_less_than_10 = location_stats[location_stats<=10]
location_stats_less_than_10
```

```
len(df5.location.unique())
df5.location = df5.location.apply(lambda x: 'other' if x in location_stats_less_than_10
else x)
len(df5.location.unique())
df5.head(10)
#Outlier Removal Using Business Logic
df5[df5.total_sqft/df5.bhk<300].head()
df5.shape
df6 = df5[~(df5.total_sqft/df5.bhk<300)]
df6.shape
#Outlier Removal Using Standard Deviation and Mean
df6.price_per_sqft.describe()
def remove_pps_outliers(df):
    df_out = pd.DataFrame()
    for key, subdf in df.groupby('location'):
        m = np.mean(subdf.price_per_sqft)
        st = np.std(subdf.price_per_sqft)
        reduced_df = subdf[(subdf.price_per_sqft>(m-st)) &
(subdf.price_per_sqft<=(m+st))]
        df_out = pd.concat([df_out,reduced_df],ignore_index=True)
    return df_out
df7 = remove_pps_outliers(df6)
df7.shape
#Let's check if for a given location how does the 2 BHK and 3 BHK property prices
look like

def plot_scatter_chart(df,location):
    bhk2 = df[(df.location==location) & (df.bhk==2)]
    bhk3 = df[(df.location==location) & (df.bhk==3)]
    matplotlib.rcParams['figure.figsize'] = (15,10)
    plt.scatter(bhk2.total_sqft,bhk2.price,color='blue',label='2 BHK', s=50)
    plt.scatter(bhk3.total_sqft,bhk3.price,marker='+', color='green',label='3 BHK', s=50)
    plt.xlabel("Total Square Feet Area")
    plt.ylabel("Price (Lakh Indian Rupees)")
    plt.title(location)
    plt.legend()
plot_scatter_chart(df7,"Rajaji Nagar")
```

```
#Let's check if for a given location how does the 2 BHK and 3 BHK property prices look like
```

```
def plot_scatter_chart(df,location):
    bhk2 = df[(df.location==location) & (df.bhk==2)]
    bhk3 = df[(df.location==location) & (df.bhk==3)]
    matplotlib.rcParams['figure.figsize'] = (15,10)
    plt.scatter(bhk2.total_sqft,bhk2.price,color='blue',label='2 BHK', s=50)
    plt.scatter(bhk3.total_sqft,bhk3.price,marker='+', color='green',label='3 BHK', s=50)
    plt.xlabel("Total Square Feet Area")
    plt.ylabel("Price (Lakh Indian Rupees)")
    plt.title(location)
    plt.legend()
plot_scatter_chart(df7,"Rajaji Nagar")
```

```
plot_scatter_chart(df7,"Hebbal")
{

            '1' : {

                'mean': 4000,

                'std: 2000,
                'count': 34

            },

            '2' : {

                'mean': 4300,

                'std: 2300,

                'count': 22  },    }

#Now we can remove those 2 BHK apartments whose price_per_sqft is less than
mean price_per_sqft of 1 BHK apartment

def remove_bhk_outliers(df):

exclude_indices = np.array([])
    for location, location_df in df.groupby('location'):
        bhk_stats = {}
        for bhk, bhk_df in location_df.groupby('bhk'):
            bhk_stats[bhk] = {
                'mean': np.mean(bhk_df.price_per_sqft),
                'std': np.std(bhk_df.price_per_sqft),
                'count': bhk_df.shape[0]
            }
        for bhk, bhk_df in location_df.groupby('bhk'):
            stats = bhk_stats.get(bhk-1)
            if stats and stats['count']>5:
                exclude_indices = np.append(exclude_indices,
bhk_df[bhk_df.price_per_sqft<(stats['mean'])].index.values)
```

```
    return df.drop(exclude_indices,axis='index')
df8 = remove_bhk_outliers(df7)
df8 = df7.copy()
df8.shape

plot_scatter_chart(df8,"Rajaji Nagar")
plot_scatter_chart(df8,"Hebbal")


import matplotlib
matplotlib.rcParams["figure.figsize"] = (20,10)
plt.hist(df8.price_per_sqft,rwidth=0.8)
plt.xlabel("Price Per Square Feet")
plt.ylabel("Count")

Text(0, 0.5, 'Count')

#Outlier Removal Using Bathrooms Feature

df8.bath.unique()
array([ 4.,  3.,  2.,  5.,  8.,  1.,  6.,  7.,  9., 12., 16., 13.])
plt.hist(df8.bath,rwidth=0.8)
plt.xlabel("Number of bathrooms")
plt.ylabel("Count")
Text(0, 0.5, 'Count')
f8[df8.bath>10]


#It is unusual to have 2 more bathrooms than number of bedrooms in a home

df8[df8.bath>df8.bhk+2]

df9 = df8[df8.bath<df8.bhk+2]
df9.shape

df9.head(2)

df10 = df9.drop(['size','price_per_sqft'],axis='columns')
```

```
df10.head(3)

#Use One Hot Encoding For Location

dummies = pd.get_dummies(df10.location)
dummies.head(3)
df11 = pd.concat([df10,dummies.drop('other',axis='columns')],axis='columns')
df11.head()
df12 = df11.drop('location',axis='columns')
df12.head(2)

#Build a Model Now...

df12.shape
X = df12.drop(['price'],axis='columns')
X.head(3)
X.shape

y = df12.price
y.head(3)

len(y)

from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X,y,test_size=0.2,random_state=10)

from sklearn.linear_model import LinearRegression
lr_clf = LinearRegression()
lr_clf.fit(X_train,y_train)
lr_clf.score(X_test,y_test)

#Use K Fold cross validation to measure accuracy of our LinearRegression model

from sklearn.model_selection import ShuffleSplit
from sklearn.model_selection import cross_val_score
cv = ShuffleSplit(n_splits=5, test_size=0.2, random_state=0)
cross_val_score(LinearRegression(), X, y, cv=cv)
```

```
#Find best model using GridSearchCV
from sklearn.model_selection import GridSearchCV
from sklearn.linear_model import Lasso
from sklearn.tree import DecisionTreeRegressor
def find_best_model_using_gridsearchcv(X,y):
    algos = {
        'linear_regression' : {
            'model': LinearRegression(),
            'params': {
                'normalize': [True, False]
            }
        },
        'lasso': {
            'model': Lasso(),
            'params': {
                'alpha': [1,2],
                'selection': ['random', 'cyclic']
            }
        },
        'decision_tree': {
            'model': DecisionTreeRegressor(),
            'params': {
                'criterion' : ['mse','friedman_mse'],
                'splitter': ['best','random']
            }
        }
    }
    scores = []
    cv = ShuffleSplit(n_splits=5, test_size=0.2, random_state=0)
    for algo_name, config in algos.items():
        gs = GridSearchCV(config['model'], config['params'], cv=cv, return_train_score=False)
        gs.fit(X,y)
        scores.append({
            'model': algo_name,
            'best_score': gs.best_score_,
            'best_params': gs.best_params_
        })

    return pd.DataFrame(scores,columns=['model','best_score','best_params'])
find_best_model_using_gridsearchcv(X,y)
#Test the model for few properties
def predict_price(location,sqft,bath,bhk):
    loc_index = np.where(X.columns==location)[0][0]
    x = np.zeros(len(X.columns))
    x[0] = sqft
    x[1] = bath
    x[2] = bhk
    if loc_index >= 0:
        x[loc_index] = 1
    return lr_clf.predict([x])[0]
predict_price('1st Phase JP Nagar',1000, 2, 2)
predict_price('1st Phase JP Nagar',1000, 3, 3)
predict_price('Indira Nagar',1000, 2, 2)
predict_price('Indira Nagar',1000, 3, 3)
#Export the tested model to a pickle file
import pickle
with open('banglore_home_prices_model.pickle','wb') as f:
    pickle.dump(lr_clf,f)
```

```
#Export location and column information to a file that will be useful later on in our prediction application
import json
columns = {
   'data_columns' : [col.lower() for col in X.columns]
}
with open("columns.json","w") as f:
   f.write(json.dumps(columns))
```

CHAPTER 5

TESTING AND RESULTS

Testing serves as a critical means to uncover potential errors within the system. It involves systematically probing for any possible faults or vulnerabilities present in the work product. The primary objective is to evaluate the functionality of individual components, subassemblies, assemblies, or the final product itself. Through testing, the software undergoes rigorous examination to ensure it aligns with its defined requirements and user expectations, thereby avoiding any unacceptable failures. Various test types are employed, each catering to specific project requirements and addressing distinct aspects of the system's functionality and performance.

5.1 TYPES OF TESTINGS

5.1.1 Unit Testing

Unit testing involves testing individual components or functions of the system in isolation to verify that they perform as expected. In the context of your project, unit testing would entail testing each function or module responsible for specific tasks, such as data collection, model selection, and prediction model training. For example, you would test the model selection function to ensure it correctly analyzes the correct model with high accuracy. Unit testing helps identify and fix errors at an early stage of development, improving the overall reliability of the system.

5.1.2 Integration Testing

Integration testing focuses on testing the interaction between different modules or components of the system to ensure they work together seamlessly. This type of testing is crucial for identifying any issues that may arise when integrating various functionalities. In our project, integration testing would involve testing the integration between the data collection module and the linear regression model, ensuring that data analyzed accurately. By performing integration testing, you can verify that the system functions correctly as a whole and that data flows smoothly between different components.

5.1.3. System Testing

System testing involves testing the entire system as a whole to verify that it meets the specified requirements and functions correctly in different scenarios. This type of testing evaluates the system's behaviour and performance under real-world conditions. For our project, system testing would entail testing the end-to-end process of collecting real estate data, analysing models, training prediction models, and generating area price. By conducting system testing, you can ensure that the system behaves as expected and delivers accurate results.

5.1.4 Regression Testing

Regression testing is performed after making changes or updates to the system to ensure that existing functionality has not been adversely affected. This type of testing helps identify and fix any regressions or unintended consequences of changes. In our project, regression testing would involve testing the system after updating the linear regression algorithm to ensure that previous predictions are still accurate. By conducting regression testing, you can maintain the reliability and stability of the system throughout its development lifecycle.

5.1.5 Performance Testing

Performance testing evaluates the performance of the system under various conditions, such as high load or large datasets, to ensure it can handle the expected workload. This type of testing assesses the system's response time, throughput, and scalability. For our project, performance testing would involve testing the system's response time when analyzing a large number of rows to ensure it meets performance requirements. By conducting performance testing, you can identify and address any performance bottlenecks or scalability issues before deploying the system.

5.1.6. Usability Testing

Usability testing assesses the usability of the system from the perspective of end-users to ensure it is intuitive and easy to use. This type of testing evaluates the system's user interface, navigation, and overall user experience. In our project, usability testing would involve conducting user testing sessions to gather feedback on the system's interface and functionality. By incorporating user feedback, you can improve the usability and user satisfaction of the system.

5.1.7. Security Testing

Security testing evaluates the system for vulnerabilities and security flaws to ensure that sensitive data is protected. This type of testing helps identify and mitigate potential security risks, such as unauthorized access or data breaches. In our project, security testing would involve performing penetration testing to identify and address any security vulnerabilities in the system. By conducting security testing, you can enhance the overall security posture of the system and protect real estate data.

5.1.8. Acceptance Testing

Acceptance testing involves testing the system against the acceptance criteria defined by stakeholders to ensure it meets their expectations and requirements. This type of testing validates that the system fulfills its intended purpose and delivers the desired outcomes. For our project, acceptance testing would involve having stakeholders review the system and provide feedback on whether it accurately predicts area price. By conducting acceptance testing, you can ensure that the system meets the needs and expectations of its users.

5.2 TEST PLAN

The test plan is a comprehensive document outlining the scope, approach, resources, and schedule of all planned test activities. It encompasses various crucial elements such as test items, specific features to be tested, allocated testing tasks, and the individuals responsible for each task. Additionally, it defines the level of independence expected from testers, the designated test environment, and the chosen test design techniques. Entry and exit criteria are established to determine when testing begins and ends, alongside the rationale behind these criteria's selection. Furthermore, the test plan includes contingency planning to mitigate any identified risks effectively. Overall, it serves as a detailed record of the entire test planning process, ensuring clarity and alignment with project objectives.

5.2.1 Analyse the System

Analysing the system involves a thorough examination of its various components, functionalities, and requirements. This process is crucial for understanding the system's architecture, its intended purpose, and how it aligns with user expectations. In the context of

Scope Definition:

Based on area price prediction using Linear Regression model, analyzing the system entails:

- Understanding the key components of the system, such as the data collection module, Linear Regression algorithm, and prediction model.
- Identifying the functionalities of each component and how they interact with one another.
- Clarifying the system's requirements, including the types of Real Estate data to be collected, the Linear Regression model to be employed, and the accuracy thresholds for prediction.
- Evaluating how well the system meets its intended purpose of predicting area price based on Linear Regression.
- Assessing any potential challenges or limitations associated with the system, such as data privacy concerns, algorithm accuracy, or scalability issues.

By thoroughly analysing the system, you can gain valuable insights into its strengths, weaknesses, and overall feasibility for achieving the project objectives.

5.2.2 Design the Test Strategy

Designing the test strategy involves outlining the overall approach and methodology for testing the system. This strategy serves as a blueprint for the testing process, ensuring that all necessary aspects are considered and addressed effectively. In the context of our project on area price prediction using Linear Regression, designing the test strategy entails:

1.Testing Objectives:

- Establishing clear testing objectives, such as validating the accuracy of sentiment analysis algorithms, assessing the performance of prediction models, and ensuring the reliability of the system under various conditions.

2.Test Environment:

- Identifying the required test environment, including hardware, software, and network configurations necessary for conducting testing activities.

3.Testing Techniques:

- Selecting appropriate testing techniques, such as unit testing, integration testing, system testing, and acceptance testing, based on the characteristics of the system and project requirements.

4.Test Data:

- Defining the test data required for testing various scenarios, including representative Real estate data sets containing data related to area , bhk , bathroom.

5.Test Coverage:

- Determining the extent of test coverage, including the breadth and depth of testing required to ensure adequate validation of the system's functionality and performance.

6.Test Execution:

- Outlining the process for executing tests, including the sequence of testing activities, allocation of resources, and responsibilities of testing team members.

7.Defect Management:

- Establishing procedures for identifying, reporting, and managing defects encountered during testing, including prioritization, tracking, and resolution.

8.Risk Management:

- Identifying potential risks associated with testing activities, such as data quality issues, algorithm inaccuracies, or resource constraints, and developing mitigation strategies to address them.

9.Exit Criteria:

- Defining the criteria for determining when testing is complete and the system is ready for deployment, including specific quality metrics and performance thresholds.

5.2.3 Define the Test Objectives

Defining the test objectives is essential for establishing clear goals and expectations for the testing process. In the context of your project on Real estate price prediction using, Linear Regression the test objectives may include:

1.Validation of Linear Regression Accuracy:

- Verify the accuracy of Linear Regression algorithms in correctly predicting the data when tested.

2.Assessment of Prediction Model Performance:

- Evaluate the performance of the prediction model in accurately predicting the area price based on Linear Regression.

3.Verification of System Robustness:

- Ensure that the system remains robust and reliable under various conditions, including fluctuations in real estate data volume, diverse areas , and real-time processing demands.

4.Validation of Data Collection Mechanism:

- Confirm the effectiveness and efficiency of the data collection mechanism in retrieving relevant areas related to real estate, bhk, and bathroom.

5.Verification of System Scalability:

- Assess the system's scalability to handle large volumes of Real estate data and accommodate increasing user demand without compromising performance.

6.Confirmation of User Acceptance:

- Validate that the system meets user expectations and requirements, as outlined in the project specifications, and delivers results that are meaningful and actionable for stakeholders.

7.Evaluation of Prediction Accuracy:

- Measure the accuracy of the system's area price predictions against ground truth data or historical price outcomes to assess its reliability and predictive capability.

5.2.4 Define Test Criteria

Defining test criteria involves establishing specific conditions or metrics that must be met to determine the success or completion of testing activities. In the context of our project on area price prediction using Linear Regression model, the test criteria may include:

1.Accuracy of Linear Regression:

- Criteria: The Linear Regression algorithm must achieve a minimum accuracy threshold (e.g., 70%) in correctly predicting price of the area.

2.Performance of Prediction Model:

- Criteria: The prediction model should demonstrate a certain level of accuracy (e.g., 75%) in forecasting price of area based on the provided dataset.

3.Robustness of the System:

- Criteria: The system must be able to handle fluctuations in real estate data volume, area contexts, and processing demands without experiencing significant performance degradation or errors.

4.Efficiency of Data Collection Mechanism:

- Criteria: The data collection mechanism should retrieve a minimum percentage (e.g., 90%) of relevant data related to house and the price related to areas within a specified time frame.

5.Scalability of the System:

- Criteria: The system should demonstrate scalability by maintaining consistent performance and response times, even when handling large volumes of real estate data or increased user demand.

6.User Acceptance:

- Criteria: The system should receive positive feedback from users, indicating that it meets their expectations, delivers meaningful results, and is easy to use.

7.Prediction Accuracy:

- Criteria: The system's price predictions should align closely with ground truth data or historical real estate, price , with a deviation of no more than a certain percentage
  (e.g., 5%).

8.Data Privacy and Security Compliance:

- Criteria: The system must adhere to data privacy regulations and security standards, ensuring that user data collected from Kaggle is protected against unauthorized access or breaches.

5.2.5 Resource Planning

Resource planning involves identifying and allocating the necessary resources, including personnel, tools, and infrastructure, to support the testing activities effectively. In the context of your project real estate price prediction using linear regression, resource planning may include:

1.Personnel:

- Identify the testing team members, including testers, analysts, and project managers, with the requisite skills and expertise in, machine learning, and data analysis.
- Allocate roles and responsibilities, specifying who will be responsible for conducting tests, analysing results, managing defects, and overseeing the overall testing process.

2.Tools and Software:

- Select appropriate testing tools and software frameworks for conducting sentiment analysis, data visualization, and performance testing.
- Ensure that the selected tools are compatible with the project requirements and can efficiently handle large volumes of real estate data.

3.Infrastructure:

- Determine the hardware and software infrastructure needed to support testing activities, including servers, databases, and cloud computing resources.

- Establish the necessary testing environments, such as development, testing, and production environments, to facilitate testing in a controlled and realistic setting.

4.Training and Development:

- Provide training and development opportunities for testing team members to enhance their skills and knowledge in areas such as machine learning algorithms, data analysis techniques, and testing methodologies.
- Encourage continuous learning and collaboration among team members to stay updated on the latest developments in Linear Regression and price prediction techniques.

5.Documentation and Reporting:

- Develop standardized templates and guidelines for documenting test plans, test cases, and test results to ensure consistency and clarity in reporting.
- Implement effective communication channels and reporting mechanisms to keep stakeholders informed about the progress, findings, and outcomes of testing activities.

6.Budget and Timeline:

- Estimate the budget required for acquiring resources, training team members, and maintaining testing infrastructure throughout the project lifecycle.
- Establish a realistic timeline for resource allocation, taking into account dependencies, constraints, and milestones associated with testing activities.

5.2.6 Plan Test Environment

Planning the test environment involves setting up the necessary infrastructure and configurations to support the testing activities effectively. In the context of your project on election result prediction using Linear Regression analysis, planning the test environment may include the following steps:

1.Infrastructure Setup:

- Determine the hardware and software requirements for the test environment, including servers, databases, and computing resources.

- Procure or allocate the necessary hardware components and ensure they meet the specifications for running the Linear Regression algorithms and prediction models.

2.Software Configuration:

- Install and configure the required software components, including the Linear Regression tools, machine learning libraries, and data visualization platforms.
- Ensure that the software versions are compatible with the project requirements and that any dependencies are resolved.

3.Data Preparation:

- Prepare the test data sets, including Real estate data containing prices related to area, bhk, bathroom.
- Cleanse and preprocess the data to remove noise, handle missing values, and standardize the format for analysis.

4.5Testing Environments:

- Establish separate testing environments for development, testing, and production to facilitate controlled testing and validation of the system.
- Ensure that each environment is isolated and configured with the necessary resources, such as access to Kaggle, storage for data sets, and computing power for analysis.

5.Security Measures:

- Implement security measures to protect sensitive data collected from Kaggle and ensure compliance with data privacy regulations.
- Restrict access to the test environment to authorized personnel only and monitor for any unauthorized activities or breaches.

6.Scalability and Performance Testing:

- Test the scalability and performance of the system by simulating varying loads of Real estate price dataset and user interactions.
- Monitor the system's response times, resource utilization, and throughput to identify any bottlenecks or performance issues.

7.Integration with External Systems:

- Integrate the test environment with external systems such as Kaggle for data collection, to ensure seamless interaction and data exchange.
- Validate the interoperability of the system with external components and verify that data flows smoothly between them.

8.Documentation and Maintenance:

- Document the configurations, setup instructions, and maintenance procedures for the test environment to ensure consistency and repeatability.

5.2.7 Schedule & Estimation

Creating a schedule and estimation plan is crucial for effectively managing testing activities. In the context of your project on real estate prediction using Linear Regression, the schedule and estimation plan may include the following components:

1.Task Breakdown:

- Break down the testing activities into smaller tasks and subtasks, such as data collection, preprocessing, Linear Regression, model training, and evaluation.
- Identify dependencies between tasks and determine the sequence in which they need to be executed.

2.Resource Allocation:

- Allocate human resources, including testers, analysts, and project managers, to each testing task based on their skills, availability, and expertise.
- Estimate the effort required for each task in terms of person-hours or person-days.

3.Time Estimates:

- Provide time estimates for each testing task, taking into account factors such as complexity, data volume, and the availability of resources.
- Use historical data or benchmarks from similar projects to guide your estimations and ensure they are realistic and achievable.

4.Milestones and Deadlines:

- Define key milestones and deadlines for completing major testing phases, such as data collection, model training, validation, and deployment.

- Set interim deadlines for completing individual tasks and subtasks to track progress and ensure timely delivery.

5.Risk Assessment:

- Identify potential risks and uncertainties that could impact the testing schedule, such as data quality issues, algorithm performance, or resource constraints.
- Develop contingency plans and mitigation strategies to address risks and minimize their impact on the testing timeline.

6.Communication and Collaboration:

- Establish regular communication channels and meetings to review progress, discuss challenges, and make any necessary adjustments to the schedule.
- Foster collaboration between team members and stakeholders to ensure alignment on priorities and expectations.

7.Tracking and Monitoring:

- Implement tools and systems for tracking and monitoring progress against the schedule, such as project management software or task boards.
- Regularly update the schedule based on actual progress and adjust estimates as needed to reflect changes in scope or requirements.

8.Documentation and Reporting:

- Document the schedule and estimation plan in a formal document or project management tool and share it with relevant stakeholders.
- Provide regular updates and reports on the status of testing activities, including progress against milestones, any deviations from the schedule, and mitigation strategies for addressing delays or issues.

5.2.8 Determine Test Deliverables

1.Test Plan:

- The test plan is a comprehensive document that outlines the entire testing process for our real estate price prediction system.
- It details the scope of testing, including the features and functionalities to be tested, as well as any dependencies or constraints.

- The test plan defines the objectives of testing, such as ensuring the accuracy of Linear Regression and the reliability of prediction models.
- It specifies the testing approach, including the methodologies, techniques, and tools to be used, as well as the roles and responsibilities of team members.
- The test plan also includes a schedule of testing activities, milestones, and deadlines, as well as criteria for entry and exit from each testing phase.

2.Test Cases and Scenarios:

- Test cases are detailed descriptions of specific test scenarios or conditions that need to be verified during testing.
- Each test case includes step-by-step instructions on how to execute the test, including inputs, actions, and expected outcomes.
- These test cases and scenarios serve as a roadmap for testers to ensure thorough coverage of all system functionalities and edge cases.

3.Test Data Sets:

- Test data sets consist of curated Real estate data that will be used for training and testing the Linear Regression algorithms and prediction models.
- These data sets include data related to real estate, house, bhk.
- Test data sets should be representative of the real-world data that the system will encounter and should cover a diverse range of areas.

4.Test Results and Reports:

- Test results and reports document the outcomes of testing activities, including the performance of Linear regression algorithms and prediction models.
- These reports include quantitative metrics such as accuracy, precision, recall, and F1-score, as well as qualitative assessments of system behaviour and usability.
- Test reports may also include visualizations such as charts, graphs, and heatmaps to illustrate trends, patterns, and anomalies in the data.

5.Validation and Verification Documents:

- Validation documents provide evidence that the prediction models produce reliable and accurate results in real-world scenarios.
- Verification documents confirm that the Linear Regression algorithms adhere to specified requirements and standards, such as accuracy thresholds and performance benchmarks.
- These documents may include test plans, test cases, test results, and validation reports to demonstrate compliance with quality standards and regulatory requirements.

6.Documentation Updates:

- Documentation updates capture any changes or enhancements to the project documentation resulting from the testing process.
- This includes updates to requirements specifications, design documents, user manuals, and other project artifacts to reflect the validated functionality and performance of the system.
- Documentation updates ensure that all stakeholders have access to the latest information about the system and its functionality.

7.Training Materials:

- Training materials provide resources for educating users, administrators, and stakeholders about the capabilities, limitations, and best practices for using the price prediction system.
- These materials may include user guides, tutorials, training videos, and FAQs to help users understand how to interact with the system and interpret the results.
- Training materials facilitate the adoption and use of the system, empowering users to leverage its capabilities effectively and efficiently.

8.Test Environment Configuration:

- Test environment configuration details the setup and configuration of the testing environment, including hardware, software, and data configurations.
- Test environment configuration ensures consistency and reproducibility in testing activities.

5.3 TEST REPORT

The testing of the system is performed for various test cases under different conditions considering most of the possible scenarios. To list a few, some of the test reports listed below.

Among the test reports provided are evaluations on user input validation, stress testing, and third-party API integration."

Test case	UTC-1
Name of the Test	Linear Regression Function Test
Item Tested	Linear Regression Function
Sample Input	This is area of 1st Phase jaya nagar, 2 bhk,2 bathroom.
Expected output	25 lakhs
Actual output	25.55 lakhs
Remarks	The price prediction function correctly predicts the price

Table 5.3.1 Unit Testing

Test case:	ITC-1
Name of the Test:	Integration between Data Collection and Linear Regression
Item Tested:	Data Collection Module, Linear Regression Module
Sample Input:	Area data
Expected output:	This is area of 1st Phase Rajaji Nagar, 2 bhk,2 bathroom.
Actual output:	20 lakhs
Remarks:	The integration between the data collection module and area analysis function works as expected.

Table 5.3.2 Integration Testing

Test case:	STC-1
Name of the Test:	End-to-End System Test
Item Tested:	Entire System
Sample Input:	This is area of 2st Phase Rajaji Nagar, 3 bhk,3 bathroom.
Expected output:	25 lakhs
Actual output:	Predicted
Remarks:	The entire system functions correctly and predicts price outcomes accurately.

Table 5.3.3 System Testing

Test case:	RTC-1
Name of the Test:	Linear Regression Function Test
Item Tested:	Linear Regression Function
Sample Input:	This is area of 2st Phase Jaya Nagar, 3 bhk, 3bathroom
Expected output:	30 lakhs
Actual output:	25.5 lakhs
Remarks:	The linear regression function retains its accuracy after updates.

Table 5.3.4 Regression Testing

Test case:	PTC-1
Name of the Test:	System Response Time Test
Item Tested:	Entire System
Sample Input:	Location, bhk, bathroom, area in (sqft)
Expected output:	Acceptable response time
Actual output:	Actual response time
Remarks:	The system responds within acceptable time limits even with a large dataset.

Table 5.3.5 Performance Testing

Test case:	FTC-1
Name of the Test:	User Interface Evaluation
Item Tested:	System User Interface
Sample Input:	N/A
Expected output:	Intuitive and easy-to-use interface
Actual output:	User feedback
Remarks:	Users find the interface intuitive and user-friendly.

Table 5.3.6 Usability Testing

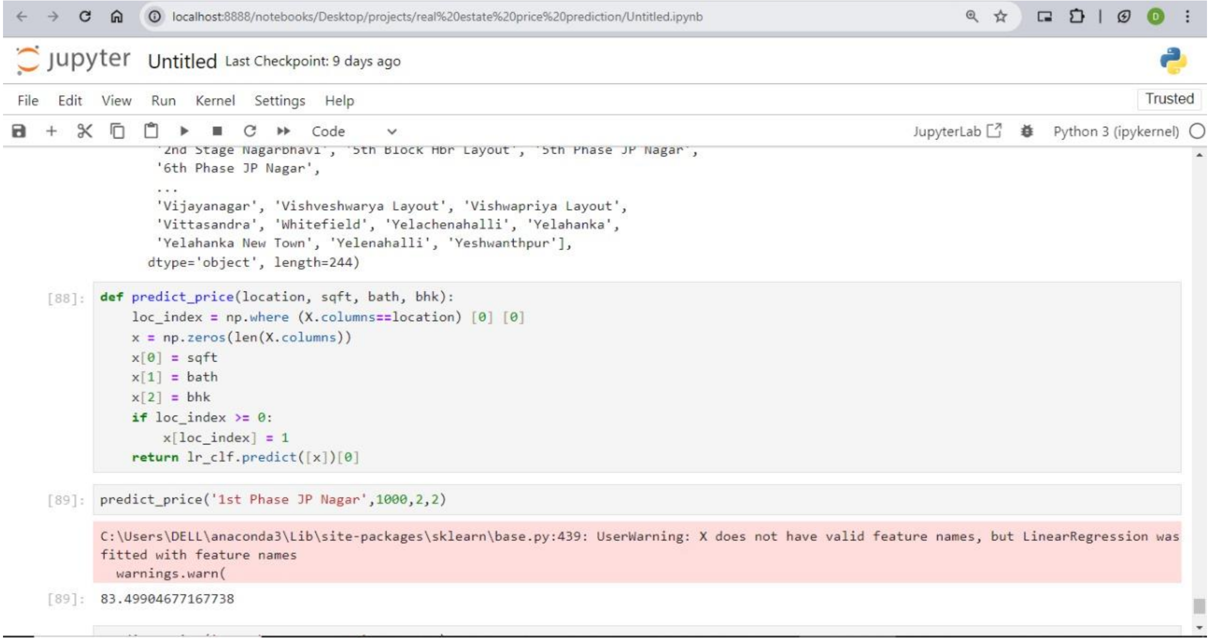
Test case:	STC-1
Name of the Test:	Penetration Testing
Item Tested:	Entire System
Sample Input:	Attempted unauthorized access
Expected output:	No security vulnerabilities found
Actual output:	Identified security vulnerabilities
Remarks:	Security vulnerabilities need to be addressed to protect sensitive data.

Table 5.3.7 Security Testing

Test case:	ATC-1
Name of the Test:	Stakeholder Review
Item Tested:	Entire System
Sample Input:	Real estate data
Expected output:	Accurate price predictions
Actual output:	Stakeholder feedback
Remarks:	Stakeholders approve the system for predicting price outcomes.

Table 5.3.8 Acceptance Testing

5.4 RESULTS


localhost:8888/notebooks/Desktop/projects/real%20estate%20price%20prediction/Untitled.ipynb
jupyter
Untitled Last Checkpoint: 9 days ago
File
Edit
View
Run
Kernel
Settings
Help
Trusted
Code
JupyterLab
Python 3 (ipykernel)

```
        '2nd Stage Nagarbhavi', '5th Block Hbr Layout', '5th Phase JP Nagar',
        '6th Phase JP Nagar',
        ...
        'Vijayanagar', 'Vishveshwarya Layout', 'Vishwapriya Layout',
        'Vittasandra', 'Whitefield', 'Yelachenahalli', 'Yelahanka',
        'Yelahanka New Town', 'Yelenahalli', 'Yeshwanthpur'],
       dtype='object', length=244)

[88]: def predict_price(location, sqft, bath, bhk):
          loc_index = np.where (X.columns==location) [0] [0]
          x = np.zeros(len(X.columns))
          x[0] = sqft
          x[1] = bath
          x[2] = bhk
          if loc_index >= 0:
              x[loc_index] = 1
          return lr_clf.predict([x])[0]

[89]: predict_price('1st Phase JP Nagar',1000,2,2)

      C:\Users\DELL\anaconda3\Lib\site-packages\sklearn\base.py:439: UserWarning: X does not have valid feature names, but LinearRegression was
      fitted with feature names
        warnings.warn(

[89]: 83.49904677167738
```

Fig 5.4.1 Giving input as (location, bhk, bedroom, area in sqft) and providing output as price.

Input Features:

Location: The geographical location of the property, which can significantly impact its market value. Factors such as proximity to urban centres, amenities, transportation hubs, and neighbourhood characteristics influence real estate prices.

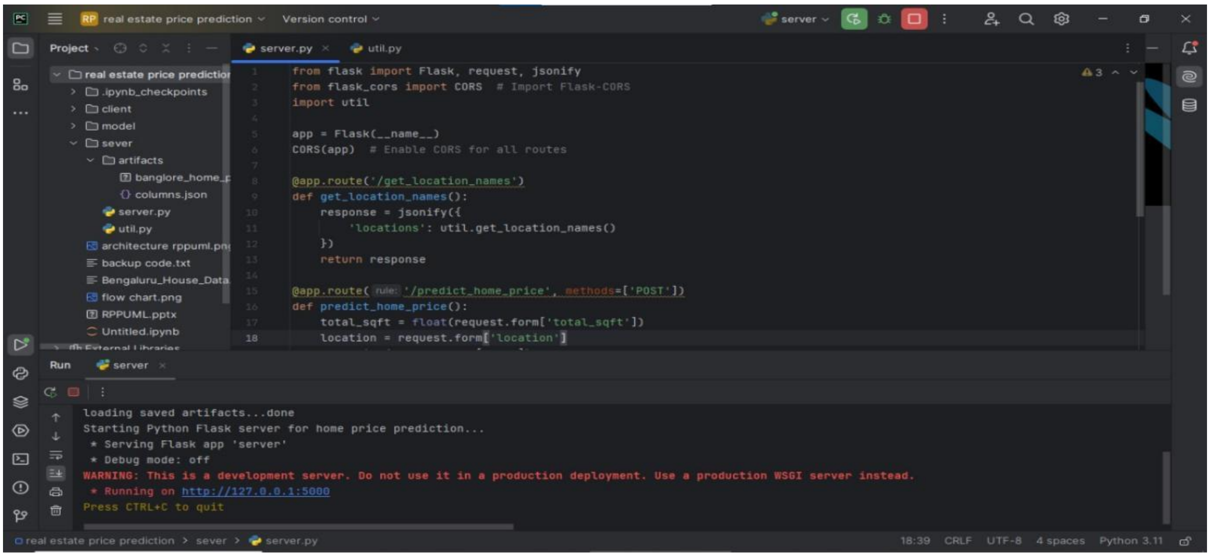
Number of Bedrooms (BHK): The number of bedrooms in the property, indicating its size and accommodation capacity. Properties with a higher number of bedrooms typically command higher prices due to increased living space.

Number of Bathrooms: The number of bathrooms in the property, which affects convenience and functionality. Properties with more bathrooms, especially ensuite bathrooms, are often valued higher for their added comfort and privacy.

Area in Square Feet (sqft): The total area of the property measured in square feet, encompassing both indoor and outdoor space. Larger properties generally have higher prices, but other factors such as layout, amenities, and land value also influence pricing.

Output:

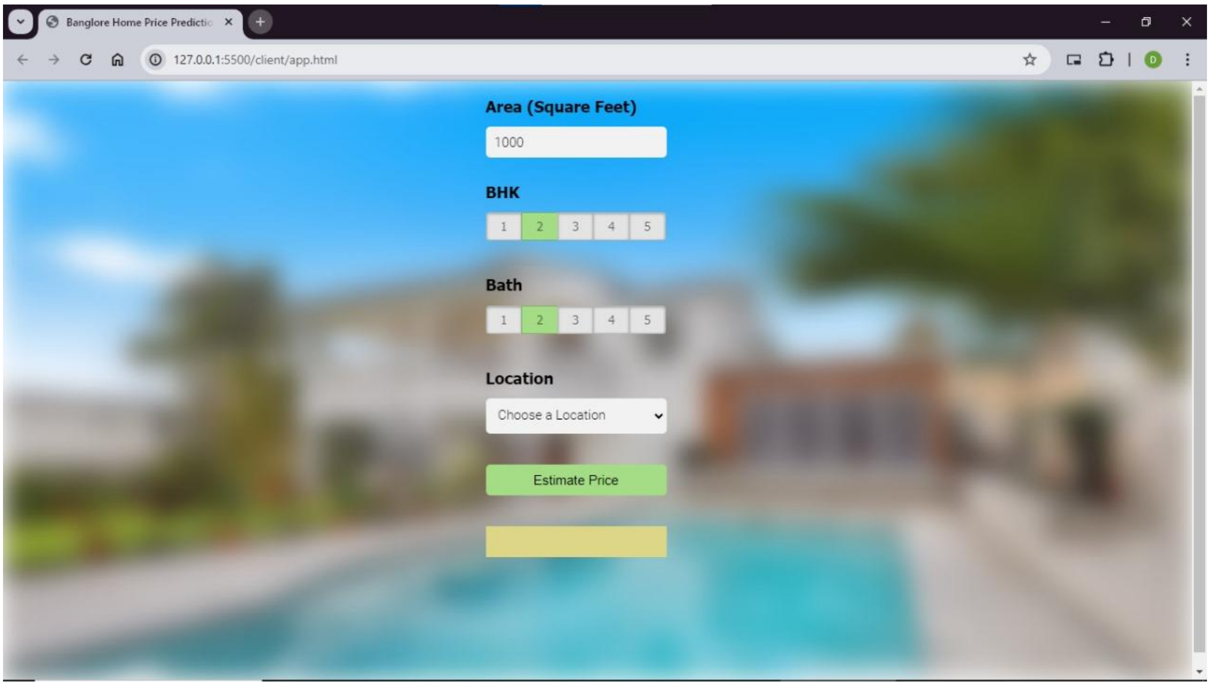
The output of the prediction model is the estimated price of the real estate property based on the provided input features. The predicted price represents the model's assessment of the property's market value given its location, size, and other relevant characteristics.



```
from flask import Flask, request, jsonify
from flask_cors import CORS  # Import Flask-CORS
import util

app = Flask(__name__)
CORS(app)  # Enable CORS for all routes

@app.route('/get_location_names')
def get_location_names():
    response = jsonify({
        'locations': util.get_location_names()
    })
    return response

@app.route( rule: '/predict_home_price', methods=['POST'])
def predict_home_price():
    total_sqft = float(request.form['total_sqft'])
    location = request.form['location']
```

```
loading saved artifacts...done
Starting Python Flask server for home price prediction...
 * Serving Flask app 'server'
 * Debug mode: off
WARNING: This is a development server. Do not use it in a production deployment. Use a production WSGI server instead.
 * Running on http://127.0.0.1:5000
Press CTRL+C to quit
```

Fig 5.4.2 wrapped the code into server and server responded giving the url.



Area (Square Feet)

1000

BHK

1 2 3 4 5

Bath

1 2 3 4 5

Location

Choose a Location

Fig 5.4.3 User Interface for Entering Input

Input Parameters:

Location: [User-inputted location]

Number of Bedrooms (BHK): [User-selected BHK count]

Number of Bathrooms: [User-selected bathroom count]

Area in Square Feet (sqft): [User-inputted area]

Predicted Price: $[Predicted price]

Insights:

The estimated price is influenced by factors such as location, property size, and market demand. Properties in [User-inputted location] tend to command higher prices due to [mention specific reasons, e.g., proximity to amenities, schools, transportation]. Larger properties with more bedrooms and bathrooms generally have higher market value.

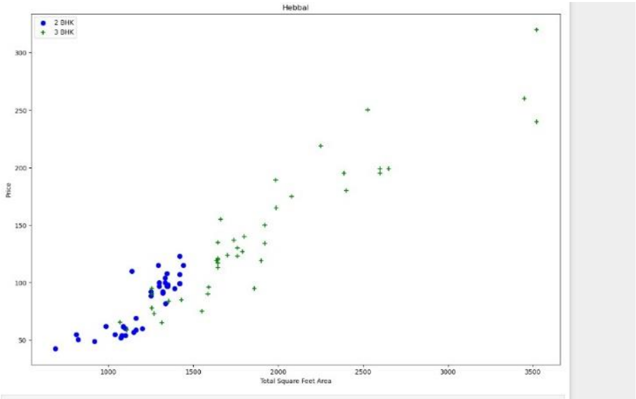


Fig 5.4.4 Linear Regression Scatter Plot after Data Cleaning

CHAPTER-6

CONCLUSION

The analysis began with data acquisition from various sources, including historical sales records, property characteristics, economic indicators, and geographic information. The employed preprocessing techniques to clean and transform the data, ensuring its suitability for modelling. Feature engineering played a crucial role in extracting meaningful insights from the raw data, incorporating factors such as location, property size, amenities, and market trends.

Several machine learning algorithms were evaluated, including linear regression, decision trees, random forests, and gradient boosting machines. Implemented cross-validation and hyperparameter tuning to optimize model performance and mitigate overfitting. Furthermore, ensemble techniques such as stacking and bagging were explored to enhance predictive accuracy and robustness.

The experimental results demonstrated promising performance across different evaluation metrics, including mean squared error, mean absolute error, and R-squared. The models exhibited the ability to capture complex relationships between input features and real estate prices, showcasing their potential for practical deployment in the market.

The study demonstrates the feasibility and effectiveness of using machine learning for real estate price prediction. By leveraging advanced analytics and computational techniques, stakeholders can gain valuable insights and make more informed decisions in the dynamic and complex real estate market.

6.1FUTURE SCOPE

1.Advanced Prediction Models: Future research can focus on developing more sophisticated machine learning models, incorporating deep learning techniques like neural networks and recurrent neural networks (RNNs). These models can capture intricate patterns and dependencies within real estate data, leading to more accurate price predictions.

2.Integration of Additional Data Sources: Incorporating diverse data sources such as satellite imagery, social media trends, economic indicators, and environmental factors can enhance the predictive capabilities of models.

3.Geospatial Analysis: Leveraging geospatial analysis techniques can offer valuable insights into spatial patterns and local market variations. By integrating geographic information systems (GIS) with machine learning algorithms, researchers can develop location-specific prediction models.

4.Dynamic Pricing Strategies: Real-time updating of pricing models can facilitate dynamic pricing strategies, allowing stakeholders to adapt to changing market conditions swiftly. By continuously analysing incoming data streams and adjusting predictions in real-time.

5.Risk Assessment and Management: Advanced risk assessment models can provide investors with actionable insights, enabling them to make informed decisions and safeguard their investments effectively.

6.Personalized Recommendations: Tailoring price predictions and investment recommendations to individual preferences and risk profiles can enhance user experience and facilitate more informed decision-making.

7.Ethical and Responsible AI: As the adoption of machine learning in real estate expands, ensuring ethical and responsible use of AI technologies becomes paramount. Future research should focus on developing frameworks for ethical AI, addressing concerns related to bias, fairness, and transparency in real estate price prediction models.

8.Industry Adoption and Integration: Encouraging widespread adoption of machine learning technologies within the real estate industry requires collaboration between researchers, industry stakeholders, policymakers, and regulatory bodies. Efforts should be made to facilitate knowledge transfer, provide training and support, and establish standards and guidelines.

CHAPTER-7

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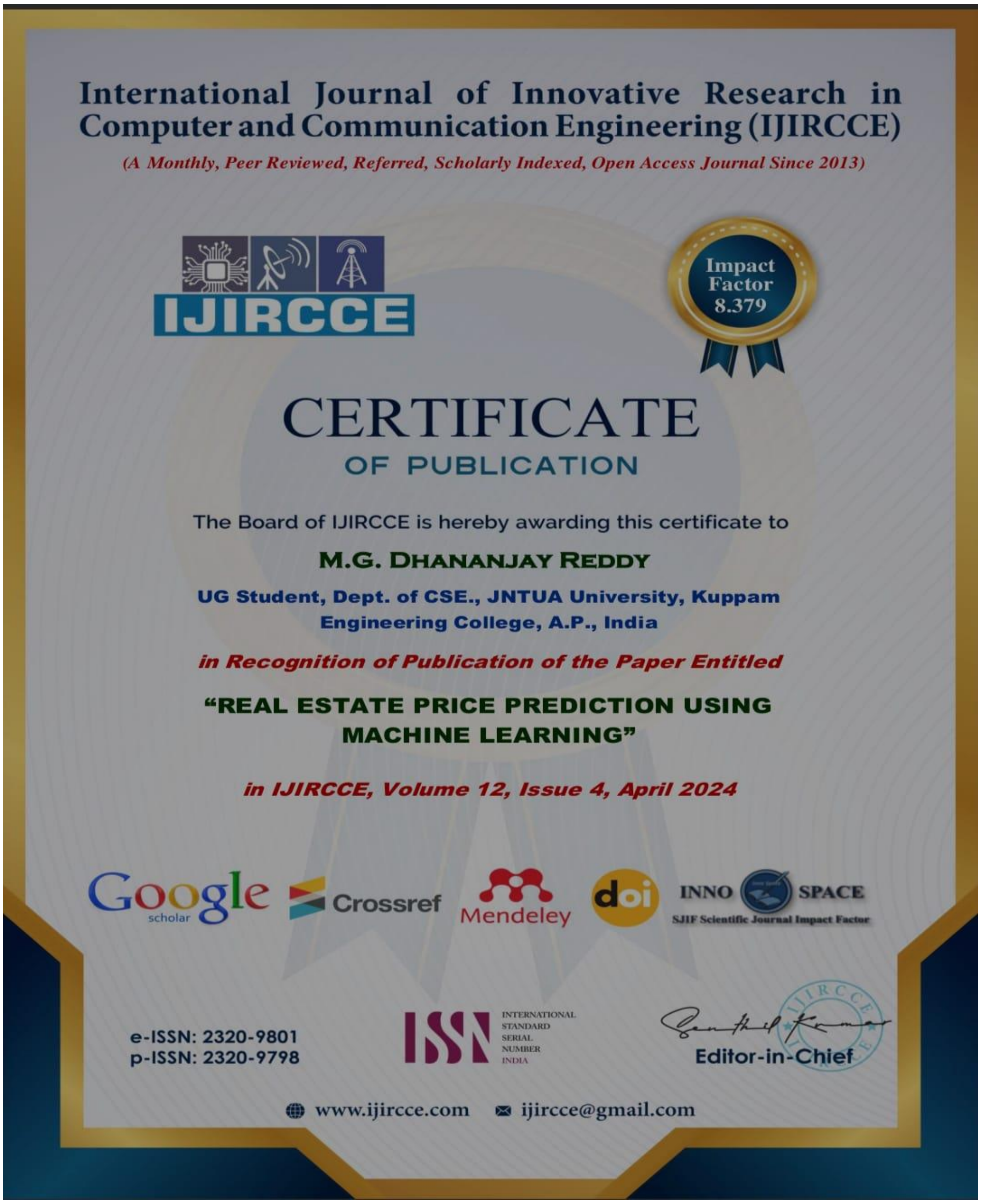
CHAPTER-8

CERTIFICATES



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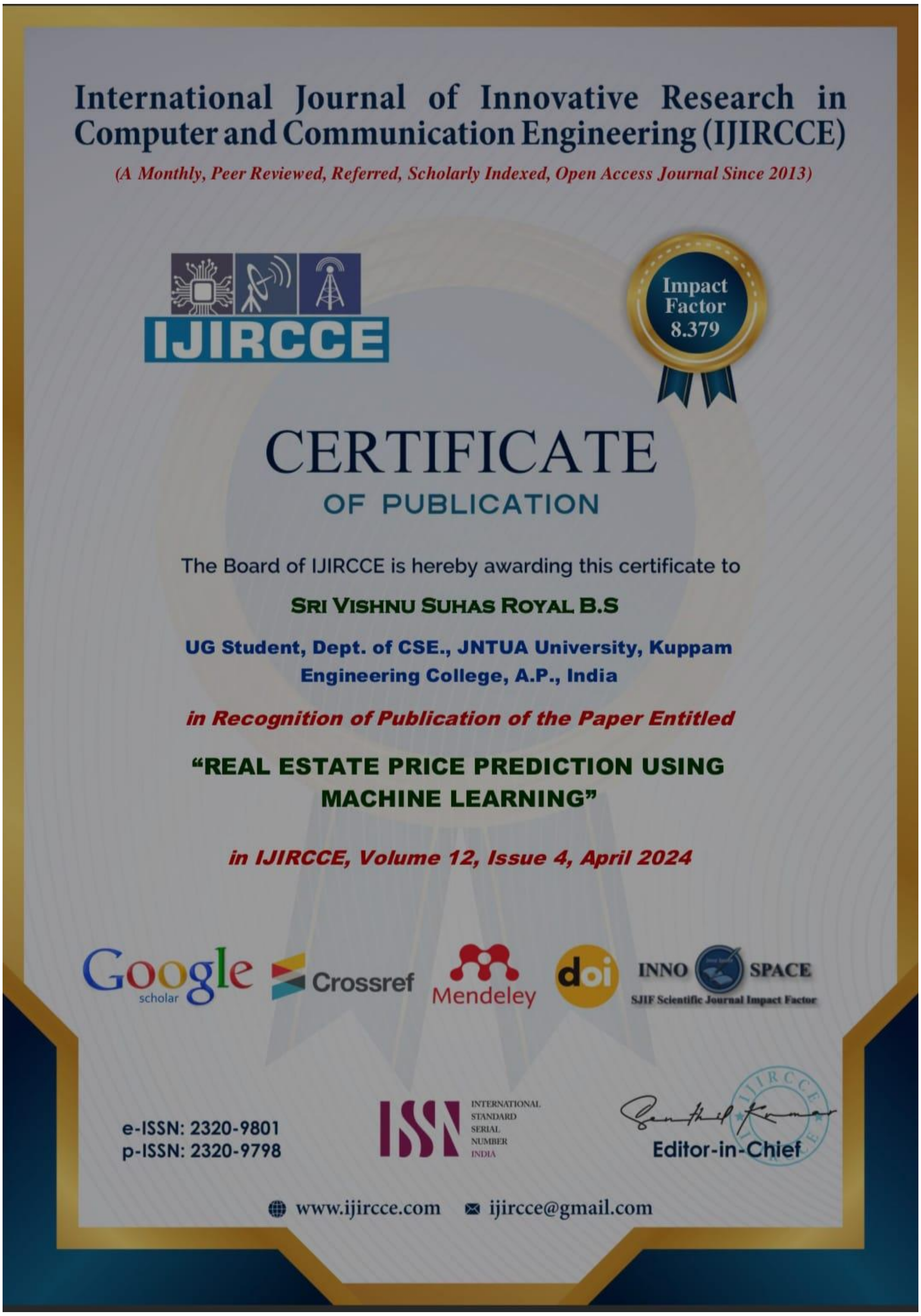

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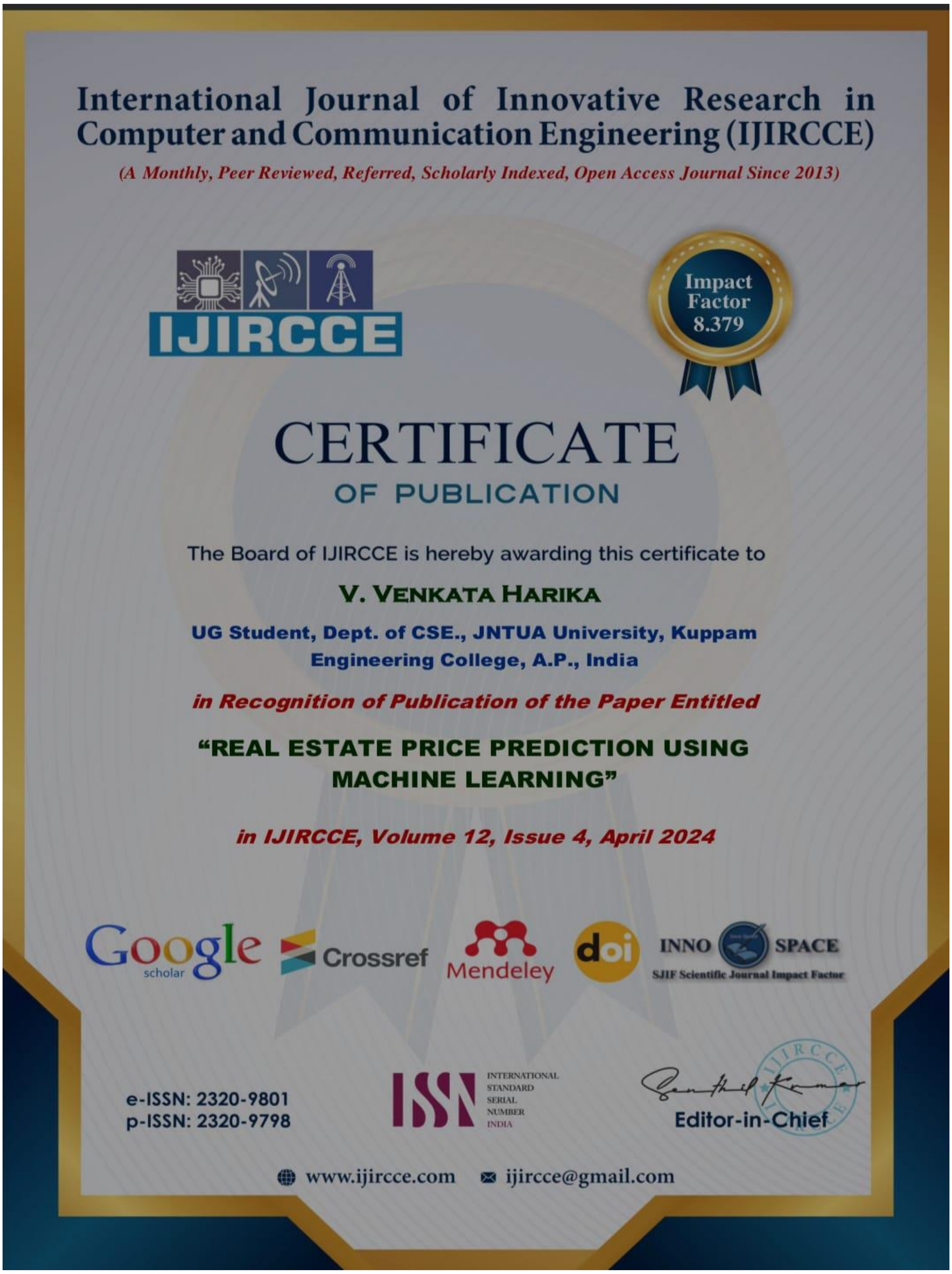

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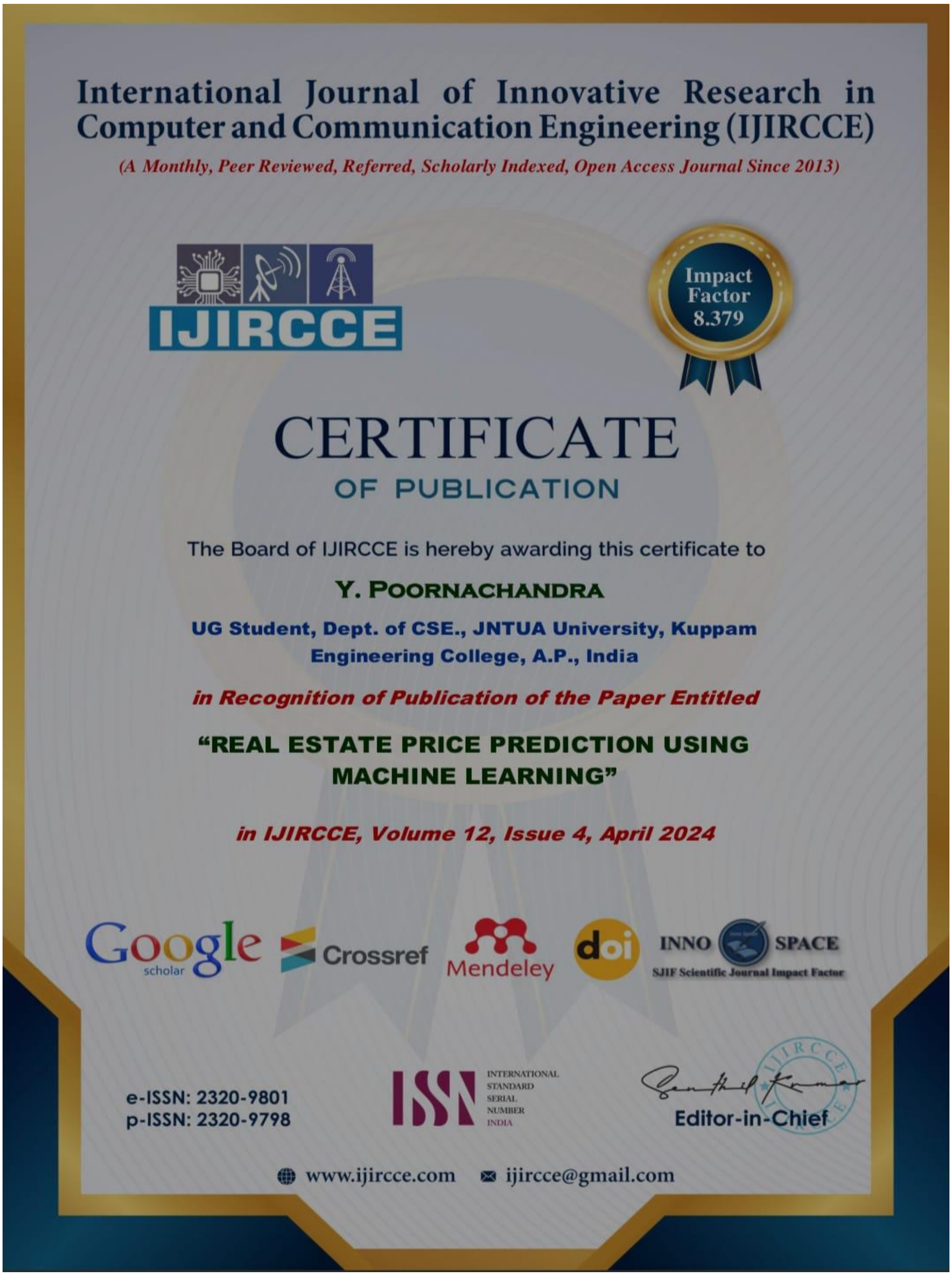

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