

# REAL ESTATE PRICE PREDICTOR

<sup>1</sup>Mr. Manoj Kumar Saini, <sup>2</sup>Rohil Khan, <sup>3</sup>Pankaj Sharma, <sup>4</sup>Sachin Jain, <sup>5</sup>Saurabh Saini

<sup>1</sup>Professor, Department of CSE, Modern Institute of Technology and Research Centre, Rajasthan, India.

<sup>2,3,4,5</sup>UG Student, Department of CSE, Modern Institute of Technology and Research Centre, Rajasthan, India

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## Corresponding Author

Rohil Khan

**Abstract**— The Real Estate Price Prediction System is a Machine Learning–based solution designed to improve the accuracy and reliability of property valuation. Traditional methods often rely on human judgment and limited data, leading to inconsistent results. This project addresses these issues by using data-driven techniques to estimate property prices more objectively. The system is built using historical real estate data, including features such as location, area, number of bedrooms, and property age. The application is deployed using FastAPI for the backend, React with TypeScript for the frontend, and Supabase PostgreSQL as the database, ensuring scalability and real-time performance. Additionally, the integration of SHAP-based explainability helps users understand the impact of different features on price predictions. Overall, the system enhances transparency, reduces human bias, and provides a scalable, efficient, and user-friendly solution for accurate real estate pricing.

**Keywords:** Machine Learning, Data Preprocessing, Feature Engineering, Model Optimization, Random Forest, Gradient Boosting, FastAPI Backend, React Frontend, TypeScript, Supabase PostgreSQL, Real-Time Prediction.

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## I. INTRODUCTION

The Real Estate Price Prediction System is a Machine Learning–based solution developed to provide accurate, consistent, and data-driven property valuations. Traditional valuation methods depend heavily on human expertise, which can lead to bias, inconsistency, and limited analysis. This system overcomes these challenges by using historical data and advanced algorithms to generate reliable price predictions.

### Key Features

- **Use of Multiple Property Factors:** The system considers important features such as location, area (square footage), number of bedrooms (BHK), property age, and available amenities.
- **Real-Time Prediction Capability:** The system is designed to process user inputs instantly and generate price estimates within seconds.

### Working Process

- **Data Collection and Preprocessing:** The system collects real estate data from reliable sources. This data is cleaned by handling missing values .
- **Model Training and Learning:** Machine learning models are trained on the processed dataset to learn patterns and relationships between property features and their corresponding prices.
- **Backend Prediction (FastAPI):** The trained model is deployed using FastAPI, which handles.

- **Frontend Interaction (React + TypeScript):** A user-friendly interface allows users to input property details easily and view predicted results in a clear format.

### Advantages

- **Scalability:** The system can be expanded to handle multiple cities, property types, and large datasets.
- **User-Friendly Design:** The intuitive interface ensures ease of use for both technical and non-technical users.

## II. PROBLEM STATEMENT

The modern real estate valuation process has become a significant source of inefficiency and uncertainty. This systemic limitation leads to inaccurate property pricing, delayed decision-making, and financial risks for buyers, sellers, and investors who rely on unreliable or inconsistent valuation methods.

### A. Lack of Accurate and Objective Valuation

Property pricing is influenced by multiple factors such as location, area, amenities, and market trends. However, traditional valuation methods depend heavily on human judgment and limited data analysis. This often results in inaccurate, inconsistent.

### B. Dependency on Experts and Intermediaries

Due to the complexity of real estate pricing, individuals are forced to depend on brokers, agents, or property experts for valuation. This dependency reduces transparency, increases costs, and may lead to manipulation .

### C. Inefficiency of Existing Solutions

Key limitations of current systems include:

- Limited use of historical and real-time data
- Inability to capture complex relationships .
- Lack of transparency in how prices are estimated
- Slow and manual evaluation processes
- Absence of real-time prediction.

### III. PROPOSED MODEL

#### A. System Pipeline Overview

The core functionality of the Real Estate Price Prediction System is based on a structured pipeline that transforms user input data into accurate property price estimates. This process is divided into key stages: Data Input, Preprocessing, Model Prediction, and Result Display. Each stage contributes to improving the accuracy, efficiency, and usability of the system..

#### B. Key Sub-processes in Detection:

- **Feature-Based Prediction:** The system uses important property features such as location, area, number of bedrooms, bathrooms, and property age to estimate prices.
- **Machine Learning Models:** Algorithms like, Random Forest, and Gradient Boosting are applied to capture both linear and complex relationships in the data.”
- **Model Optimization:** Hyperparameter tuning and training techniques are used to improve prediction accuracy and performance.

#### C. Data Processing and Preparation::

- **Data Preprocessing:** Handles missing values, removes outliers, and standardizes the dataset for better model performance
- **Feature Engineering:** Transforms raw data into meaningful features, such as encoding categorical variables like location..
- **Normalization:** Ensures numerical features are scaled appropriately to improve model efficiency.

#### D. Model Prediction and Explainability:

Following extraction, Hugging Face LLM models and a Vector Database generate concise, meaningful summaries prioritizing safety-critical information such as warnings, ingredients, and usage instructions.

#### E. Proposed Work Model Diagram

The overall system workflow represents a complete pipeline starting from user input, followed by data validation, preprocessing, model prediction, and finally displaying the estimated property price on the user interface in real time.

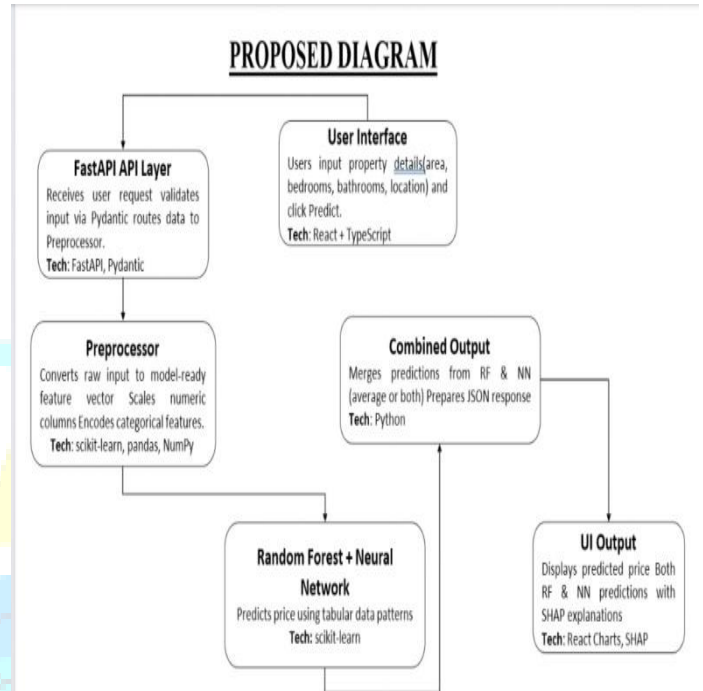


Fig. 1. Proposed Model

### IV. TECH STACK

The selection of an appropriate technology stack is a crucial architectural decision that determines the performance, scalability, and real-time capabilities of the system. For the Real Estate Price Prediction System, a modern and efficient stack is adopted to ensure accurate predictions, smooth user interaction, and high performance..

#### A. Frontend Technologies

The frontend is developed using React with TypeScript, providing a dynamic, responsive, and component-based user interface. It allows users to easily input property details such as area, bedrooms, bathrooms, and location. The interface is designed to be simple, intuitive, and user-friendly, ensuring smooth interaction and real-time display of prediction results..

#### B. Backend Technologies

The backend is built using FastAPI, a high-performance Python framework known for its speed and asynchronous capabilities. It handles API requests, processes user input, and communicates with the trained machine learning models to generate real-time predictions efficiently.

#### C. AL / ML Technologies

- **Machine Learning Models:** Algorithms such as, Random Forest, and Gradient Boosting are used for accurate price prediction.
- **Data Processing:** NumPy and Pandas are used for data manipulation, preprocessing, and feature engineering.
- **Model Explainability:** SHAP (Shapley Additive Explanations) is integrated to interpret how different features influence the predicted price.

### D. Prediction & API Integration

The trained model is deployed through FastAPI endpoints, enabling real-time inference. The system processes user inputs and returns predicted property prices instantly, ensuring low latency and efficient performance.

### E. Database Technology

Supabase PostgreSQL is used as the database for storing user inputs, prediction results, and logs. Its cloud-based architecture ensures scalability, reliability, and easy data management for future improvements.

The image represents the front-end interface of the Real Estate Price Prediction system, showcasing how users interact with the application. It highlights the input section where property details are entered for generating predictions. The layout reflects a modern and visually engaging design aimed at enhancing user experience. Overall, it demonstrates the system's focus on simplicity, accessibility, and real-time interaction for accurate property price estimation..

## V. RESULT SCREENSHOTS

The following screenshots demonstrate the complete end-to-end pipeline of the Real Estate Price Prediction system.



Fig. 2. Swagger

The image shows the API interface of the Real Estate Price Predictor built using FastAPI. It includes endpoints for health check, location data, and price prediction, allowing smooth interaction with different system functionalities. The structured layout makes it easy for users and developers to access and test various features

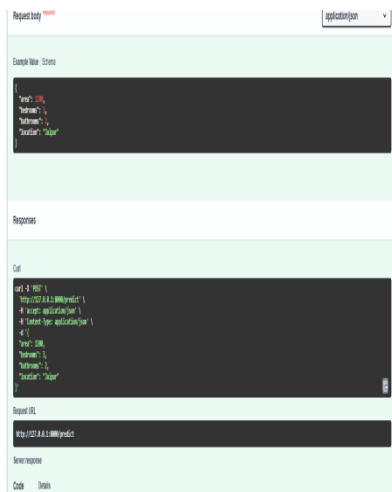


Fig. 3. Request and Response Body

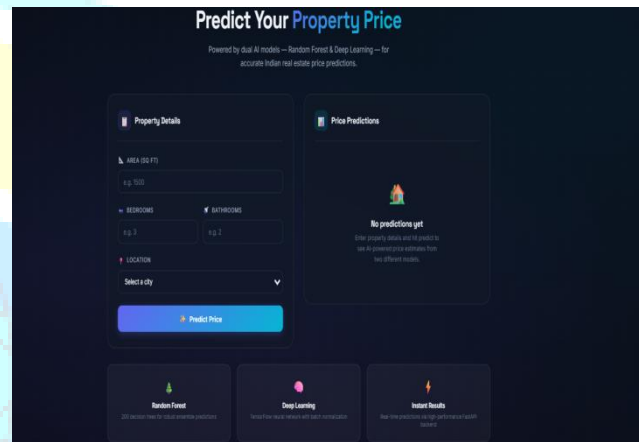


Fig. 4. Frontend

The image shows the front-end interface of the Real Estate Price Prediction system with a modern and visually appealing design. It includes input fields for property details such as area, bedrooms, bathrooms, and location, allowing users to easily enter data. The interface also displays a prediction section where estimated prices will appear after submission. Additionally, it highlights the use of Random Forest and Deep Learning models, emphasizing real-time and accurate price prediction capabilities.

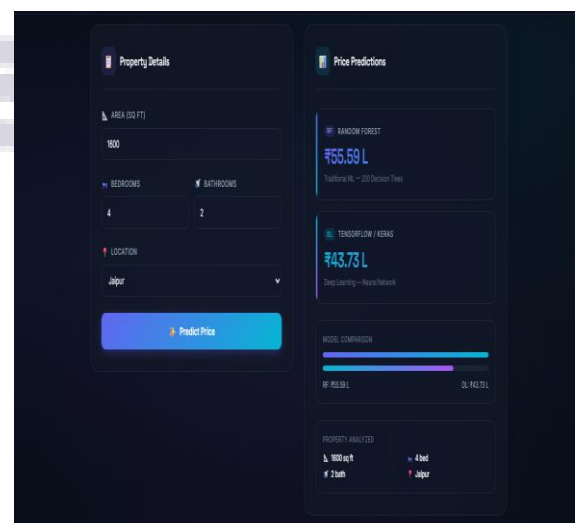


Fig. 5. Final Output

Real Estate Price Prediction system where users input property details such as area, number of bedrooms, system, bathrooms, and location. After submitting the data, the system generates price predictions using both Random Forest and Deep Learning models.

## A Project Synthesis

The development of the Real Estate Price Prediction System represents a successful integration of modern web technologies and advanced Machine Learning techniques. As the project reaches completion, its primary objective—to provide accurate, data-driven, and real-time property valuation—has been effectively achieved. The system eliminates the limitations of traditional methods by offering an automated and unbiased approach to price estimation.

The system transforms user-provided property details into reliable price predictions through a well-structured pipeline involving data preprocessing, feature engineering, and model inference. By adopting a modular architecture, the computational workload of machine learning models is efficiently separated from the user interface, ensuring smooth performance and responsiveness.

## B Core Achievements

The project has successfully delivered its key objectives:

- **Accurate Prediction:** Implementation of advanced algorithms like Linear Regression, Random Forest, and Gradient Boosting ensures precise property valuation.
- **User-Friendly Interface:** A simple and interactive UI allows users to input property details easily and obtain instant results.
- **Real-Time Performance:** Integration of FastAPI enables fast and efficient prediction with minimal latency.
- **Transparency with Explainability:** SHAP-based analysis helps users understand how different features influence the predicted price.
- **Scalability:** The system can handle large datasets and can be extended to multiple cities and property types.

## C Future Scops

Although the current system is robust and efficient, future improvements can further enhance its capabilities. Potential extensions include integration of real-time market data, support for more advanced deep learning models, inclusion of additional features like nearby facilities and crime rates, and deployment as a mobile application. These advancements will make the system more intelligent, adaptive, and suitable for large-scale real-world applications.

The system can also be enhanced by incorporating advanced machine learning and deep learning models to capture more complex patterns in property pricing. Additionally, integrating geospatial analysis using map-based data can provide better insights by considering nearby facilities such as schools, hospitals, and transportation.

Further development can include creating a mobile application to make the system more accessible and convenient for users. The system can also be expanded to support multiple cities or even global markets, increasing its scalability. Features like personalized property recommendations based on user preferences and budget can improve user experience. Moreover, implementing continuous model retraining with updated data will ensure long-term accuracy and reliability. Overall, these enhancements can transform the system into a powerful and intelligent real estate analytics platform.

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