

House Price Prediction

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Abstract: A side from being one of the fastest-growing sectors in the economy, the real estate industry serves as a significant contributor to national development and urban planning. House price prediction is very important since it directly influences investment decisions, affordability, and economic growth in metropolitan cities. In order to estimate and manage property values effectively, accurate prediction models are absolutely necessary. Traditionally, the value of a property is determined by real estate agents or manual comparison methods. This approach involves professionals who analyze past sales, location, and size manually. Such a process is labor-intensive, time-consuming, and often subjective in nature. The same property may be priced differently by multiple agents due to inconsistent evaluation criteria. Due to the dependency on human expertise, this procedure is also costly and lacks reliability. If not properly analyzed, inaccurate property valuation can lead to financial loss for both buyers and sellers, and may disrupt market stability. Hence, it becomes essential to adopt a data-driven method that can monitor and estimate house prices with precision. An alternate solution to manual valuation may be provided by machine learning algorithms, which can efficiently analyze various housing features and historical data to predict property prices. Such an approach minimizes human bias and provides consistent results at a lower cost. It in corporate features election, data preprocessing, and regression-based modeling techniques such as Linear Regression and Decision Tree Regressor to forecast the price of houses in Bangalore. Furthermore, the system can be enhanced to recommend ideal pricing strategies and investment suggestions based on market trends and neighborhood characteristics. In addition to improving prediction accuracy, the integration of machine learning in real estate price estimation also facilitates smarter decision-making for stakeholders such as buyers, sellers, and investors. By leveraging data analytics, users can gain deeper insights into property trends, demand fluctuations, and emerging growth zones.

INTRODUCTION

The "Smart Home Value Predictor" initiative was inspired by the growing need for accurate and data-driven property valuation in the real estate market. Traditional property appraisal techniques often rely on manual assessment and expert judgment, which can be subjective, inconsistent, and time-consuming. Inaccurate pricing can lead to financial losses, unfair transactions, and inefficient investment decisions. Taking note of these challenges, the initiative aims to utilize the untapped potential of historical property data and advanced machine learning algorithms to predict house prices accurately. Through the application of cutting-edge machine learning techniques to analyze various property features such as location, size, number of bedrooms and bathrooms, age, and market trends the study seeks to provide reliable price estimates. This approach not only permits accurate property valuation for buyers and sellers but also allows real estate professionals and investors to make informed decisions based on data rather than intuition. "Smart Home Value Predictor" ultimate goal is to equip users with predictive tools that improve market transparency, reduce financial risk, and support smarter investment strategies in an increasingly complex housing market. House price prediction using machine learning is an innovative approach that leverages algorithms capable of learning patterns from historical data to enhance decision-making in real estate. Property values are influenced by numerous factors, and early detection of trends and price shifts is critical for effective planning and investment. Traditional appraisal methods depend heavily on human expertise, which can be limited and subjective. By employing machine learning models such as regression algorithms, decision trees, and neural networks it becomes feasible to automate the prediction process. These models can analyze large datasets, extracting meaningful relationships between property attributes and their market value. This automated system not only improves the accuracy and speed of price prediction but also allows for real-time analysis of market trends.

Consequently, implementing machine learning in house price prediction contributes to a more transparent and efficient real estate market, reducing reliance on subjective appraisals and promoting data-driven investment decisions. The rapid advancement of technology, coupled with the exponential growth of data availability, has opened new avenues for innovation in property valuation and real estate analytics. With the increasing digitization of real estate records, online property listings, and government-maintained databases, vast amounts of information are now accessible for analysis. The Smart Home Value Predictor takes advantage of this data driven era to build intelligent systems capable of processing and interpreting large datasets efficiently. By leveraging techniques such as data preprocessing, feature engineering, and predictive modeling, the system aims to deliver highly accurate and consistent property value estimations. In traditional real estate valuation, human appraisers often face challenges in maintaining uniformity due to personal bias, limited access to comparative data, and time constraints. These limitations can lead to inconsistencies in pricing across similar properties, thereby creating inefficiencies in the housing market. The adoption of machine learning models offers a transformative solution by minimizing subjective bias and enabling automated, scalable, and replicable analyses. This shift from manual to automated valuation represents a major step forward in improving transparency, fairness, and reliability in real estate transactions. Furthermore, the Smart Home Value Predictor emphasizes the integration of multiple influencing factors to ensure holistic and accurate valuation.

II. LITERATURE REVIEW

The real estate market is a critical component of the economy, with property prices influenced by numerous factors such as location, area, number of bedrooms, age of the property, amenities, and prevailing market trends. Accurate property price prediction is essential for buyers, sellers, and investors to make informed decisions. Traditionally, property valuation relied on manual appraisal, comparative market analysis, and expert judgment. However, these methods can be subjective, time consuming, and prone to inconsistencies, especially in rapidly changing market conditions. To overcome these limitations, machine learning algorithms have been increasingly applied to predict property prices. Models such as Linear Regression, Decision Trees, Random Forests, Gradient Boosting, Support Vector Machines (SVM), and Artificial Neural Networks (ANN) have demonstrated significant improvements in prediction accuracy. These algorithms can analyze historical data, detect patterns, and capture complex relationships between property features and market prices. Recent research emphasizes the use of neural networks for capturing non-linear relationships between property features, which are often missed by traditional linear models.

Advantages:

Only analyzed disease affected parts.

The accuracy of the model heavily depends on the quality and completeness of the dataset; missing or inconsistent data can lead to unreliable predictions. To address these challenges, researchers have applied machine learning and data analytics techniques for property valuation. By leveraging historical property data, predictive models can identify patterns and correlations between property features and prices. Common algorithms include Linear Regression, Decision Trees, Random Forests, Support Vector Machines (SVM), Gradient Boosting, and Neural Networks. Advanced models like deep neural networks are capable of capturing complex nonlinear relationships that traditional methods may overlook. The objective of these house price prediction systems is to assist non-expert users such as first-time home buyers or small-scale investors in estimating property prices accurately and efficiently. Data-driven models provide instant and reliable predictions, reducing dependency on manual appraisal and expert intervention. Feature selection and engineering play a key role in model accuracy, as choosing relevant property attributes directly impacts the predictive performance. This analytical perspective not only enhances transparency but also empowers stakeholders to make proactive decisions based on factual evidence rather than speculation. Moreover, combining predictive modeling with real-time analytics can further improve market forecasting, helping policymakers, developers, and investors anticipate future price movements and optimize their strategies accordingly. data analytics with machine learning enables the visualization and interpretation of housing market trends, making the system more insightful and user-oriented

Disadvantages:

Requires large and comprehensive datasets for training to achieve high accuracy. Performance depends heavily on quality and completeness of input data

EXISTING SYSTEM

The existing house price prediction systems typically employ a combination of feature selection, data preprocessing, and classical machine learning algorithms such as Linear Regression, Decision Trees, or Support Vector Machines (SVM) to estimate property values. These models often fail to incorporate external influencing factors such as infrastructure development, inflation rates, or policy changes, which can significantly impact property values. Additionally, user interaction in existing systems is often limited, with minimal visualization or interpretability of results, making it difficult for non-technical users to understand how predictions are derived.

Feature Selection and Data Preprocessing:

These systems rely on historical property data, including features like location, size, number of bedrooms and bathrooms, age, and nearby amenities. Data preprocessing involves cleaning the dataset, handling missing values, and normalizing features to improve model performance. Feature selection is performed to identify the most relevant attributes that influence property prices, reducing dimensionality and computational complexity.

Machine Learning Algorithms:

What are the components of the future and after preprocessing, classical algorithms such as Linear Regression, Decision Trees, Random Forests, and SVM are applied to predict house prices.

SVM is particularly used in some implementations for its ability to handle high-dimensional datasets and find optimal separating hyper planes. The models are trained on historical property data to learn the relationship between features and property prices. Once trained, they can predict prices for new listings based on the input property attributes.

Disadvantages

Manual interventions are required for feature selection and data preprocessing.

Irrelevant or less significant features may still affect prediction accuracy.

Limited datasets reduce the generalization capability of the models.

Mostly regression-based models do not fully capture complex non-linear relationships in the data.

PROPOSED SYSTEM

The proposed system aims to transform the process of property valuation by providing an automated, accurate, and efficient house price prediction platform. This system is essential for buyers, sellers, and real estate professionals, as it allows them to make informed decisions based on data-driven insights rather than subjective judgments. The system utilizes advanced data processing and feature engineering techniques to extract high-level attributes of properties, focusing on critical features such as location, area, number of bedrooms and bathrooms, age, and nearby amenities. These attributes are essential for accurately estimating property prices, providing the foundation for robust predictive modeling. Central to the system is the use of advanced machine learning algorithms, including neural networks, gradient boosting, and ensemble models, which are capable of capturing complex non-linear relationships among property features. By employing these algorithms, the system can analyze historical property data with high accuracy, learning patterns that influence market prices and improving prediction precision. To enhance model performance, the proposed system can integrate pre-trained models or leverage transfer learning from large real estate datasets. Pre-training on extensive datasets allows the model to retain general market knowledge, which can then be fine-tuned for the specific regional or local property market. This approach not only accelerates the training process but also improves prediction accuracy, resulting in more reliable and actionable price estimates. Furthermore, based on the predicted prices, the system aims to provide actionable insights, such as investment recommendations, comparative market analysis, and pricing strategy suggestions. By linking property features with data-driven predictions, the system empowers users to make proactive decisions in buying, selling, or investing in real estate, optimizing financial outcomes.

System Overview: The proposed system is designed to automate the property valuation process using machine learning. It replaces traditional subjective valuation methods with data-driven prediction models. It provides reliable and real-time price estimation for residential properties. Provides predicted property prices with confidence levels.

System Architecture: Gathers property data from multiple sources such as real estate listings, public records, and user inputs. Preprocessing and Feature Engineering Cleans data, handles missing values, and creates meaningful features (e.g., price per square foot, proximity to amenities). Machine Learning Model Uses algorithms such as Neural Networks, Gradient Boosting, Random Forest, and Ensemble Models for accurate prediction.

Advantages

The system automates feature extraction and analysis, reducing human error and bias in property valuation. It enables accurate prediction of property prices by capturing complex patterns and relationships among multiple features

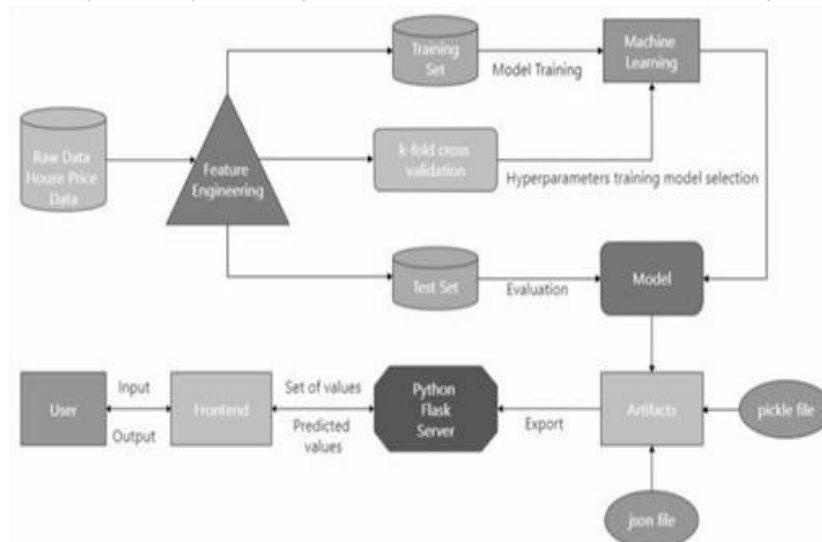


Fig.1. Architecture Diagram

SYSTEM SPECIFICATION

Hardware Requirements:

- ❖ Processor : DualCoreProcessor2.6GHzorhigher
- ❖ RAM :4GBorhigher
- ❖ Hard Disk :500GB
- ❖ Keyboard :Standard Keyboard
- ❖ Monitor :15-inchColorMonitor

Software Requirements:

- ❖ Operating System: Windows10/Windows11/Ubuntu
- ❖ Programming Language: Python3.8orlater
- ❖ Machine Learning Libraries: Scikit-learn, Tensor Flow, Pandas, NumPy
- ❖ Development Environment: Jupyter Notebook/VSCode
- ❖ Database: MySQL or SQLite for storing housing datasets
- ❖ Frame works: Flask or Django for web application development
- ❖ Visualization Tools: Matplotlib, Seaborn, Plotly for data visualization

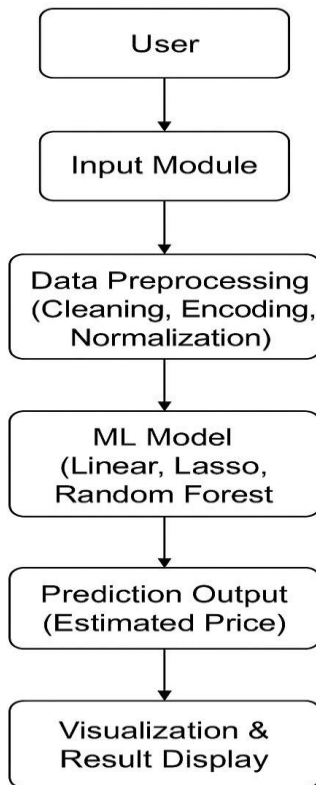


Fig.2.DataFlowDiagram

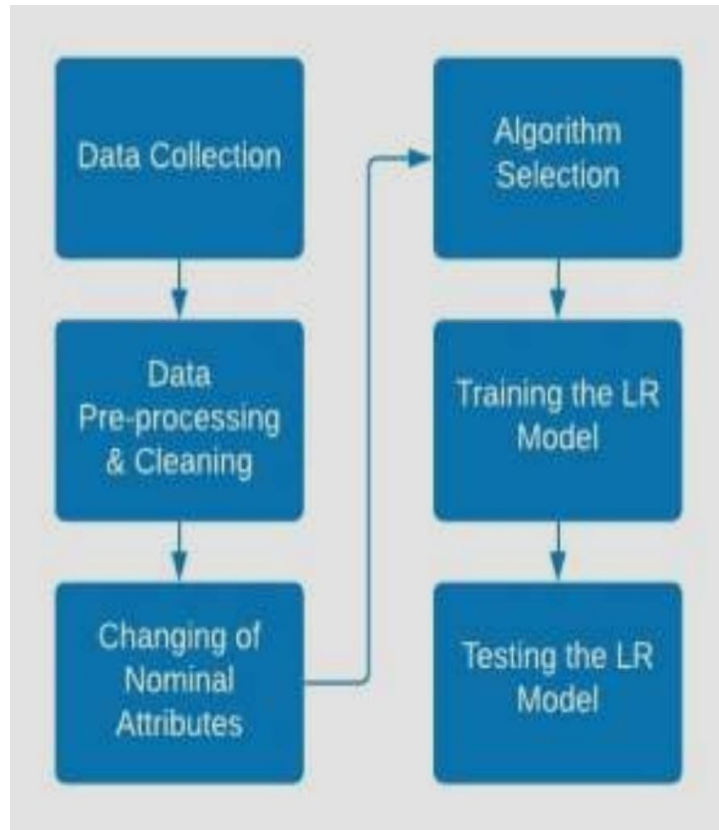


Fig.3. Flow Graph

The Data Flow Diagram (DFD) for the House Price Modules

Prediction System Using Machine Learning outlines the sequential flow of data from input to predicted property prices. The process begins with users submitting property details through a web or desktop interface. These inputs serve as the primary data for the system. Once submitted, the property data is subjected to preprocessing, which includes handling missing values, normalization, and feature engineering to extract critical attributes such as location, property size, number of bedrooms and bathrooms, age of the property, and proximity to amenities. This preprocessing transforms raw data into a structured format suitable for analysis. Next, the processed data is fed into a pre-trained machine learning model such as a neural network, gradient boosting, or ensemble model which forms the core of the system's prediction engine. The model processes the input features to estimate the market value of the property, leveraging patterns learned from historical transaction data. After prediction, the system generates an output that includes the estimated property price along with relevant insights, such as comparative market analysis, price trends, and investment suggestions.

1. Data Acquisition
2. Preprocessing & Feature Engineering
3. Feature Extraction
4. Prediction / Regression
5. Price Estimation
6. Investment Recommendation

MODULES DESCRIPTION:

1. Data Acquisition

The Data Acquisition module collects property-related data for price prediction. Data can be gathered from historical property transaction datasets, online real estate portals, government records, or user inputs through the application interface. Key preprocessing steps include handling missing values, removing duplicates, standardizing formats (e.g., numerical values for area, categorical encoding for property type or location), and normalizing feature scales. Ensuring data quality, completeness, and consistency is critical for accurate price predictions.

This module is essential for providing the machine learning system with reliable input data, forming the foundation for accurate property price estimation and informed decision-making for buyers, sellers, and investors.

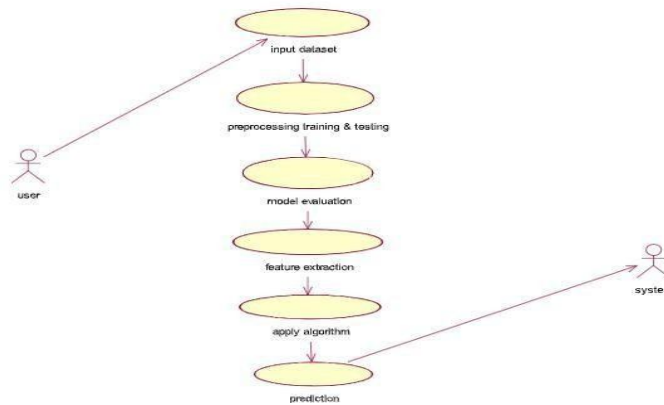


Fig.4. Use case diagram

Preprocessing & Feature Engineering

The Preprocessing & Feature Engineering module enhances the quality of property data before feeding it into the machine learning model. Key steps include: Handling Missing Values: Filling or removing missing property attributes such as area, number of bed rooms, or age. Data Cleaning: Removing duplicates, correcting inconsistent entries, and standardizing formats for numerical and categorical features.

Normalization / Scaling: Adjusting numerical features to a consistent scale, such as property area or price per square foot, to improve model performance.

Encoding Categorical Variables: Converting features like property type, location, or amenities into numerical representations using one-hot encoding or label encoding.

Feature Engineering: Creating additional features such as price per square foot, age of property, or proximity to key amenities to provide more predictive power.

Scalability and Integration: Feature selection is performed to identify the most relevant attributes that influence property prices, reducing dimensionality and computational complexity.

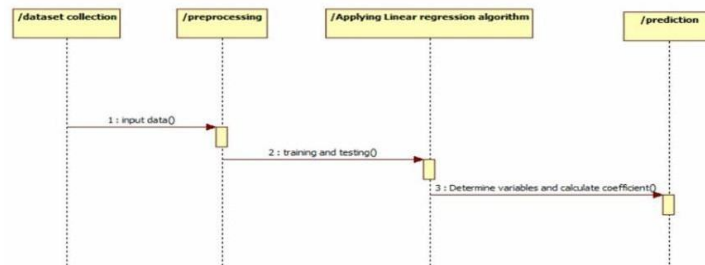


Fig.5. Sequence diagram

Feature Extraction

The Feature Extraction module focuses on selecting and transforming relevant attributes from the processed dataset that most strongly influence property prices. This step helps improve model accuracy and efficiency by reducing redundant or irrelevant data.

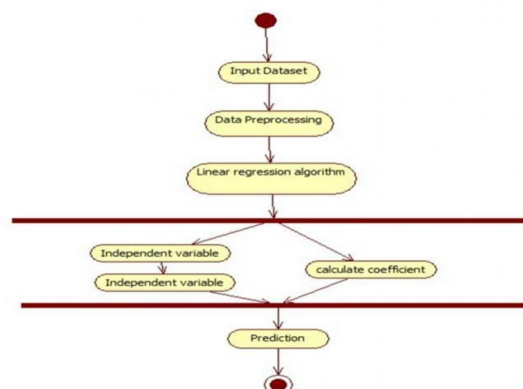


Fig.6. Activity diagram

Key processes include: Dimensionality Reduction: Using techniques such as Principal Component Analysis (PCA) or feature selection algorithms to minimize irrelevant attributes while retaining essential information. Correlation Analysis: Identifying highly correlated features to remove redundancy and ensure that only unique, meaningful features contribute to the prediction. Domain-based Feature Selection: Selecting features based on real estate domain knowledge, such as location rating, property age, area, and nearby facilities. Feature Importance Ranking: Using model-based methods (e.g., Random Forest feature importance, mutual information) to rank and retain the most influential predictors. This module ensures that the machine learning model focuses on the most valuable features, improving computational efficiency and prediction performance.

Prediction/Regression

The Prediction or Regression module is responsible for training and testing machine learning models to predict property prices based on extracted features. It applies supervised learning algorithms suited for continuous value prediction. Key steps include:

Model Selection: Choosing suitable regression algorithms such as Linear Regression, Random Forest, Decision Tree, Gradient Boosting, or Support Vector Regression (SVR).

Training and Validation: Dividing the dataset into training and testing subsets to evaluate model accuracy and prevent over fitting. Hyperparameter Tuning: Optimizing model parameters using techniques like Grid Search or Cross-Validation to achieve the best performance. Model Evaluation: Measuring prediction accuracy using metrics such as Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and R² Score. This module forms the core of the system, where machine learning algorithms learn from historical data to predict property values effectively.

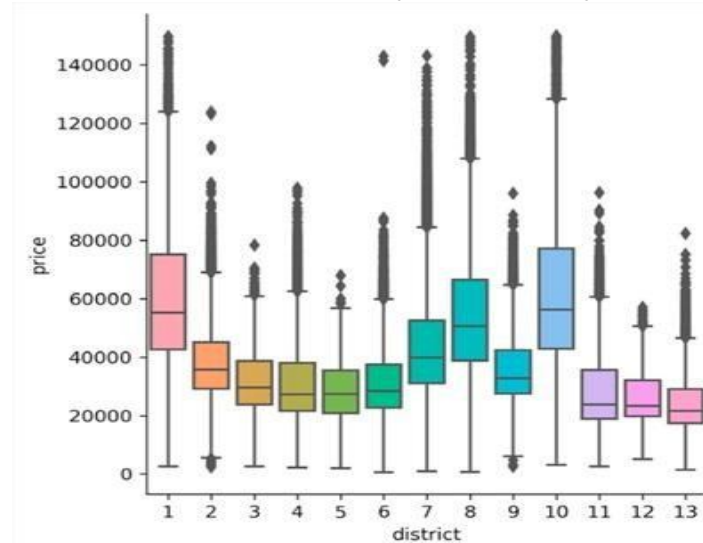


Fig.7 .Correlation between District and Price

Price Estimation

The Price Estimation module provides users with an accurate estimate of a property's market value based on the model's output. Key functions include:

Real-time Estimation: Generating predicted prices for user- specified property details like location, area, type, and amenities.

Visualization: Displaying estimated prices with comparative charts, trends, or similar property listings for better understanding.

Dynamic Updates: Continuously improving estimation accuracy through new data inputs and model retraining.

Confidence Level Indicators: Showing prediction confidence or possible price ranges to help users understand the reliability of the estimate. This module enables practical application of the trained model, allowing users to make data-driven property decisions with transparent and explainable results.

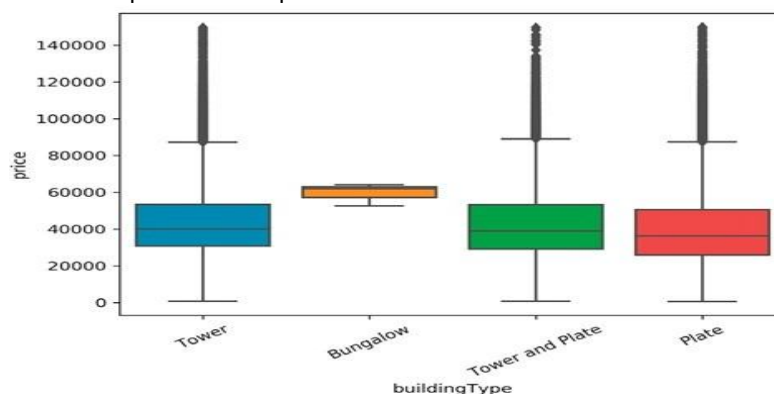


Fig.8. Correlation between Building Type and Price

Investment Recommendation

The Investment Recommendation module assists users, investors, and real estate agents in making profitable investment decisions based on predicted prices and market trends. Key functions include:

Profitability Analysis: Identifying properties with high potential for price appreciation or rental yield.

Comparative Insights: Recommending properties by comparing estimated prices, location growth rates, and nearby infrastructure developments.

Risk Assessment: Evaluating investment risk based on historical market volatility, property demand, and neighbour hood stability. **Personalized Suggestions:** Providing tailored recommendations according to the user's budget, preferences, and investment goals. This module transforms the predictive insights into actionable intelligence, guiding investors toward financially sound and strategic real estate decisions.

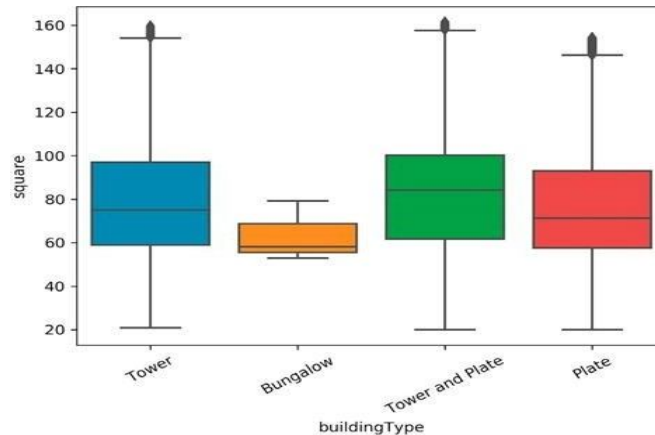


Fig.9. Correlation between Building Type and Price

SYSTEM IMPLEMENTATION

The system is designed to assist buyers, sellers, and real estate professionals in accurately estimating house prices, thereby enhancing decision-making and investment strategies. The implementation begins with the collection of a diverse property dataset, capturing various features such as location, area, number of bedrooms and bathrooms, age of the property, nearby amenities, and historical transaction prices. These datasets undergo preprocessing, which includes handling missing values, normalization, scaling, and encoding of categorical variables. Feature engineering is applied to derive additional predictive attributes such as price per square foot or distance to key locations. These steps improve model robustness and mitigate potential biases in the data. The core of the system is a machine learning model, such as a neural network, gradient boosting, or ensemble model, chosen for its effectiveness in regression and prediction tasks. The architecture typically comprises multiple layers capable of learning complex, non-linear relationships between property features and market prices. The dataset is divided into training, validation, and testing sets to evaluate the model's performance accurately. During training, the model learns to recognize intricate patterns in property data by adjusting weights based on back propagation and minimizing a loss function such as Mean Squared Error (MSE). Hyper parameter Tuning is conducted to optimize parameters like learning rate, batch size, number of layers, and number of epochs, ensuring the model achieves high accuracy and generalization capability. Once trained, the model can predict property prices for new, unseen listings in real-time.

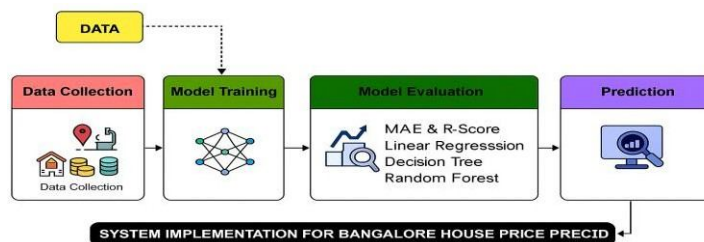


Fig.10. Implementation diagram

The system interface is designed to be user-friendly, providing users with an easy way to input property details and receive instant price estimates along with additional insights, such as comparative market trends and investment recommendations. The project also emphasizes scalability and accessibility, allowing integration with web and mobile platforms to reach a broader audience. The trained model is evaluated using metrics such as MAE and R² Score to ensure accuracy and reliability. Once validated, it is deployed through a user-friendly web interface, allowing real-time house price predictions.

CONCLUSION

The House Price Prediction System Using Machine Learning represents a significant advancement in leveraging artificial intelligence to improve real estate valuation and decision making. By utilizing advanced machine learning algorithms, including neural networks and ensemble models, this system provides a robust and efficient solution for accurately estimating property prices, offering a scalable alternative to traditional manual appraisal methods.

The use of data-driven predictions not only speeds up the valuation process but also ensures more precise and objective estimates, which is crucial for buyers, sellers, and investors in making informed financial decisions. The implementation of this system can lead to more reliable investment strategies, optimized pricing, and enhanced transparency in real estate transactions. Throughout the project, the machine learning models demonstrated the capability to predict property prices with high accuracy, underscoring the potential of AI in real estate analytics. However, the system's performance is highly dependent on the quality, completeness, and diversity of the input datasets. This reinforces the need for continuous data collection, model retraining, and feature updates to ensure adaptability across different regions, property types, and market conditions. In conclusion, the House Price Prediction System is not just a technological tool but a practical solution that can revolutionize real estate valuation by providing real-time, accurate price estimates. Its scalability, combined with potential future enhancements such as integration with web and mobile platforms, real-time market trend analysis, and continuous learning makes it a valuable asset for buyers, sellers, and investors.

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