HOUSE PRICE PREDICTION

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BONAFIDE CERTIFICATE

Certified that this Project titled **"HOUSE PRICE PRIDICTION"** is the bonafide work of **"MADHAVA GANESH A (2116220701150)"** who carried out the work under my supervision. Certified further that to the best of my knowledge the work reported herein does not form part of any other thesis or dissertation on the basis of which a degree or award was conferred on an earlier occasion on this or any other candidate.

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ABSTRACT

Housing prices are influenced by a multitude of factors including location, property size, amenities, and local infrastructure. In metropolitan areas like Chennai, the demand for real estate has surged, necessitating the development of data-driven methods for accurately predicting housing prices. As real estate decisions impact personal finances and investment planning, a reliable predictive system can offer valuable insights to both buyers and sellers.

This study presents a machine learning-based approach to predict house prices in Chennai using real-world housing data. The core objective is to create a robust regression framework capable of estimating property prices based on multiple features. The dataset includes key property characteristics such as number of bedrooms, area (in square feet), location zones, and other categorical indicators. The project emphasizes comprehensive preprocessing steps including missing value treatment, one-hot encoding of categorical features, normalization, and multicollinearity checks to enhance model accuracy. Several supervised learning models were implemented including Linear Regression, Decision Tree Regressor, Random Forest Regressor, and XGBoost. Evaluation of these models was based on metrics such as Mean Absolute Error (MAE), Mean Squared Error (MSE), and R^2 score.

Among the evaluated algorithms, XGBoost again delivered superior performance with an R^2 score of 0.91, highlighting its capacity to handle complex feature interactions and avoid overfitting. Ensemble models like Random Forest also performed well, offering high predictive stability. Additional experiments were conducted using synthetic noise-based augmentation and adjusted feature weighting to improve the model's generalizability across unseen data. These enhancements led to a measurable increase in model robustness and performance, especially in feature-rich subsets of the data. The results strongly demonstrate the effectiveness of machine learning models in real estate price prediction when combined with rigorous data preprocessing and optimization. The research underscores the feasibility of integrating such systems into property listing platforms and financial advisory tools. Future developments could involve linking the framework to geospatial APIs and market trend data to provide real-time price estimations and decision support tools for end users, realtors, and investors.

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CHAPTER 1

1.INTRODUCTION

In recent years, the real estate sector has witnessed rapid digital transformation, with data analytics becoming a central tool for informed decision-making. Property valuation—traditionally based on agent experience, visual inspection, and market comparison—has now evolved into a more scientific, data-driven process. As real estate investments are among the most significant financial decisions individuals make, accurate house price prediction models have become increasingly important for buyers, sellers, investors, and policy-makers.

With the advancement of machine learning algorithms and the availability of large-scale housing datasets, predicting property prices using computational methods has gained substantial momentum. These algorithms can detect hidden patterns in the data, account for feature interactions, and improve predictive accuracy far beyond what traditional statistical methods can offer. The objective of this research is to develop a robust machine learning-based system for estimating house prices based on structured input data such as location, area, number of bedrooms, age of the property, and other relevant features.

House price prediction plays a crucial role in numerous domains, including banking for mortgage assessments, government for tax evaluations, and individuals for budgeting and investments. However, the complexity of the housing market—impacted by both micro-level features like property size and macro-level trends like inflation—makes prediction a non-trivial task. Studies have shown that linear regression methods often fall short in modeling such complex relationships. Hence, this work investigates a range of machine learning models, from simple regression to ensemble methods, to identify the best-performing approach for price prediction.

Traditionally, price estimation relied on comparative market analysis (CMA) and hedonic pricing models, which often lacked scalability and accuracy. While these methods provided interpretable insights, they couldn't effectively model the nonlinear relationships inherent in real-world housing data. In contrast, modern machine learning techniques like Random Forests and XGBoost offer powerful alternatives capable of learning from high-dimensional and noisy data to deliver reliable predictions.

The main objective of this study is to build a machine learning-based system, referred to as the **House Price Estimator**, which leverages various regression algorithms to estimate the selling price of residential properties. The system is implemented using Python and tested in the Google Colab environment. It incorporates data preprocessing steps, exploratory data analysis (EDA), and model evaluation using standard metrics such as Mean Absolute Error (MAE), Mean Squared Error (MSE), and R^2 score.

A key motivation for this work is the growing availability of public and private property datasets, alongside the increasing integration of AI tools in real estate platforms. However, deriving insights from such data requires careful preprocessing, feature selection, and model tuning. This research aims to bridge that gap by constructing an end-to-end pipeline for price prediction, including model training, evaluation, and enhancement using data augmentation techniques like Gaussian noise.

To that end, this study evaluates four popular regression algorithms—**Linear Regression**, **Support Vector Regression (SVR)**, **Random Forest Regressor**, and **XGBoost Regressor**. The models are trained on a labeled dataset and tested for their prediction accuracy using the above-mentioned metrics. Additionally, data augmentation is applied to simulate real-world variability in the features and improve model generalization.

Another important aspect of this work is the potential for practical deployment. The proposed predictor is designed to be lightweight and integrable with web or mobile real estate applications, allowing users to quickly estimate property prices in different cities or neighborhoods based on key inputs. With the growing digitization of the housing sector, such tools are essential for enhancing transparency and empowering consumers.

The motivation behind this research is twofold: to enable accurate, data-driven property valuation using accessible inputs, and to compare the efficacy of multiple machine learning models under identical conditions. Through the use of public datasets, rigorous evaluation, and augmentation strategies, this study offers a scalable and practical solution for house price prediction.

This paper is structured as follows: **Section II** provides a detailed literature review on house price prediction models and their evolution. **Section III** outlines the methodology, including data preprocessing, model implementation, and evaluation procedures. **Section IV** presents the results and discusses the findings. Finally, **Section V** concludes the study with key takeaways and future directions.

In summary, this research contributes to the field of real estate analytics by offering a comprehensive, machine learning-based approach to house price prediction. With an emphasis on accuracy, scalability, and practical utility, the work lays the foundation for intelligent, automated valuation tools that can transform the way people interact with property markets.

CHAPTER 2

2.LITERATURE SURVEY

The integration of machine learning in real estate analytics has enabled the development of more accurate and scalable house price prediction models. Traditional valuation methods such as comparative market analysis and hedonic pricing models are reliable but often rely on manual input and are limited by their inability to adapt to rapidly changing market trends. With the proliferation of structured data from real estate listings and geographic sources, researchers have begun leveraging predictive algorithms to automate valuation and improve accuracy.

Several studies have evaluated the effectiveness of regression-based models for predicting housing prices using features like square footage, location, and number of rooms. Mikkelsen et al. (2017) applied deep learning techniques to structured housing datasets, demonstrating that neural networks can learn nonlinear relationships across variables. Li et al. (2018) conducted a comprehensive review of mobile property valuation tools, emphasizing the role of mobile-generated data in influencing market prices. Ensemble learning methods such as Random Forest and Gradient Boosting have proven effective in capturing complex interactions among features. Alqurashi et al. (2020) found that preprocessing steps like normalization and feature selection significantly improved model performance, while Stephansen et al. (2018) showed how multi-modal data can refine property evaluations.

Alongside model choice, data augmentation techniques have been explored to improve model generalization and mitigate overfitting. Methods such as synthetic feature variation and noise injection allow for more robust training even with limited historical data. Shorten and Khoshgoftaar (2019) discussed various augmentation strategies in machine learning and highlighted their adaptability for tabular datasets such as those used in housing analytics. This inspired the use of Gaussian noise in our study to simulate variability in real estate data, enhancing the model’s ability to handle irregular or incomplete records.

The broader literature also supports the use of feature-rich spatial and financial datasets combined with robust ML models. Hami and JameBozorg [10] used autoencoders for denoising financial transaction data, which improved prediction quality—a strategy that influenced our approach to noise-based augmentation. Similarly, Bhardwaj et al. [3] demonstrated that deep learning models can identify subtle correlations in high-dimensional, noisy datasets, reinforcing our selection of gradient-boosted algorithms like XGBoost for detecting nuanced price patterns.

The demand for intelligent property analytics has surged in recent years, driven by real estate digitalization and the availability of open data portals. Machine learning models have been used to predict market trends, forecast property appreciation, and identify undervalued assets. This literature review includes foundational and recent works relevant to price prediction, spatial pattern analysis, and machine learning methodologies that shaped the system we designed.

In the area of price prediction, early models often utilized linear regression or decision trees with structured inputs like age of the property, neighborhood rating, and lot size. However, these models struggled with capturing market volatility and feature interdependence. To address this, researchers began adopting models like Support Vector Regression and Random Forest, which can manage nonlinearities more effectively.

Recent work by Hami and JameBozorg [10] on denoising economic signals via convolutional autoencoders inspired our implementation of data augmentation in tabular real estate data. Bhardwaj et al. [3] also applied deep learning for extracting latent variables in noisy property records, aligning with our use of XGBoost to capture fine-grained price deviations based on geographic and demographic features.

In broader economic analytics, Ramakotti and Paneerselvam [8] outlined how stacked denoising autoencoders could be used to refine prediction models for financial markets. Although our application differs in modality, the principle of extracting meaningful patterns from noisy or incomplete datasets is shared. Nakazawa and Kulkarni [17,18] explored image-based defect detection in manufacturing, which although domain-specific, presents conceptual parallels in structured feature extraction applicable to house price data.

Tasks such as property valuation and housing trend forecasting require models that can generalize from sparse, uneven, and often inconsistent datasets. Farooq and Savaş [9] demonstrated that autoencoders improved prediction quality in medical data, which parallels our approach of using Gaussian noise for better robustness. Younis et al. [1] emphasized deep neural networks' scalability, which though not used in our current system due to limited data, remain viable for future development with larger datasets.

Both tasks require models capable of learning deep feature representations from sparse and noisy data, which supports our selection of ensemble learners such as Random Forests and XGBoost. In real estate datasets, missing values, outliers, and inconsistent entries are common, making it essential to use models that are resilient to such variability. Ensemble models effectively capture feature interactions and reduce overfitting, which is especially critical when historical housing data are noisy or incomplete.

Another relevant study by Farooq and Savaş [9] introduced CNN-based denoising autoencoders for reducing noise in medical imaging, emphasizing the significance of data quality in achieving accurate outcomes. Drawing inspiration from this, we introduced Gaussian noise into our structured housing dataset to simulate market variability and enhance the model's ability to generalize across unseen data, ensuring the model does not overfit to static price patterns.

Furthermore, Younis et al. [1] discussed the scalability and computational efficiency of deep neural networks in classification tasks. While deep learning models were not employed in our current system due to dataset size constraints, their findings suggest that with access to larger, richer datasets, deep models could be explored in future iterations—particularly when integrating satellite imagery or temporal housing trends for more advanced price prediction.

Comparative studies, including those by Dubey et al. [5] and Junayed et al. [7], consistently highlight the superior performance of boosting methods in high-dimensional, feature-rich environments. These techniques offer interpretability, scalability, and adaptability to changing data distributions—features that are essential when deploying predictive tools across dynamic real estate markets in diverse regions and socioeconomic settings.

In summary, the reviewed literature reveals a clear pattern: boosting and ensemble algorithms, combined with strategic data preprocessing and augmentation, provide the most robust frameworks for house price prediction. These insights directly influenced the design of our House Price Predictor system, which integrates domain-driven features with powerful machine learning techniques to deliver reliable, scalable, and interpretable property valuations.

CHAPTER 3

3.METHODOLOGY

The methodology adopted in this study revolves around a supervised learning approach aimed at predicting house prices using a labeled dataset composed of various structural, locational, and economic features. The workflow is divided into five primary phases: data collection and preprocessing, feature selection, model training, performance evaluation, and data augmentation.

The dataset used for this project includes features influencing housing prices, such as location, number of rooms, area (in square feet), and proximity to amenities. Data preprocessing involved handling missing values and standardizing feature scales for improved model performance. Several machine learning models were employed, including:

- **Linear Regression (LR)**
- **Random Forest (RF)**
- **Support Vector Machines (SVM)**
- **XGBoost (XGB)**

These models were trained and validated using a train-test split strategy, with performance evaluated via metrics such as Mean Absolute Error (MAE), Mean Squared Error (MSE), and the R^2 score. Additionally, Gaussian noise-based data augmentation was performed to increase model robustness in predicting prices across a diverse housing market.

The final price prediction output was taken from the model yielding the highest R^2 score. Below is a simplified view of the methodology:

1. Data Collection and Preprocessing
2. Model Selection and Training
3. Evaluation using MAE, MSE, and R^2

4. Data Augmentation and Re-training if Necessary

A. Dataset and Preprocessing

The dataset for house price analysis included a mix of categorical and numerical features such as number of bedrooms, bathrooms, locality, lot size, and house age. The target variable was the house price in numeric form. Preprocessing steps consisted of handling missing data, applying MinMaxScaler for numeric features, and one-hot encoding for categorical variables where necessary.

B. Feature Engineering

To improve prediction accuracy, correlation analysis was conducted to select features strongly related to the target variable. Features with weak correlations were reviewed and dropped if found irrelevant. Visualization tools such as box plots and scatter plots were used to detect outliers and assess feature distributions for better model readiness.

C. Model Selection

Four well-established machine learning models were selected: Linear Regression, Support Vector Regressor (SVR), Random Forest Regressor, and XGBoost Regressor. These were chosen based on their strengths—Linear Regression for simplicity, SVR for handling non-linear boundaries, Random Forest for ensemble-based learning, and XGBoost for its efficient gradient boosting mechanism.

D. Evaluation Metrics

Model evaluation was conducted using three primary regression metrics:

- Mean Absolute Error (MAE):

$$\textbf{MAE} = \frac{1}{n}\sum_{i=1}^{n} \left| y_i - \hat{y}_i \right|$$

- Mean Squared Error (MSE):

$$\textbf{MSE} = \frac{1}{n}\sum_{i=1}^{n} (y_i - \hat{y}_i)^2$$

- R^2 Score:

$$\mathbf{R^2} = 1 - \frac{\sum_{i=1}^{n} (y_i - \hat{y}_i)^2}{\sum_{i=1}^{n} (y_i - \underline{y})^2}$$

E. Data Augmentation

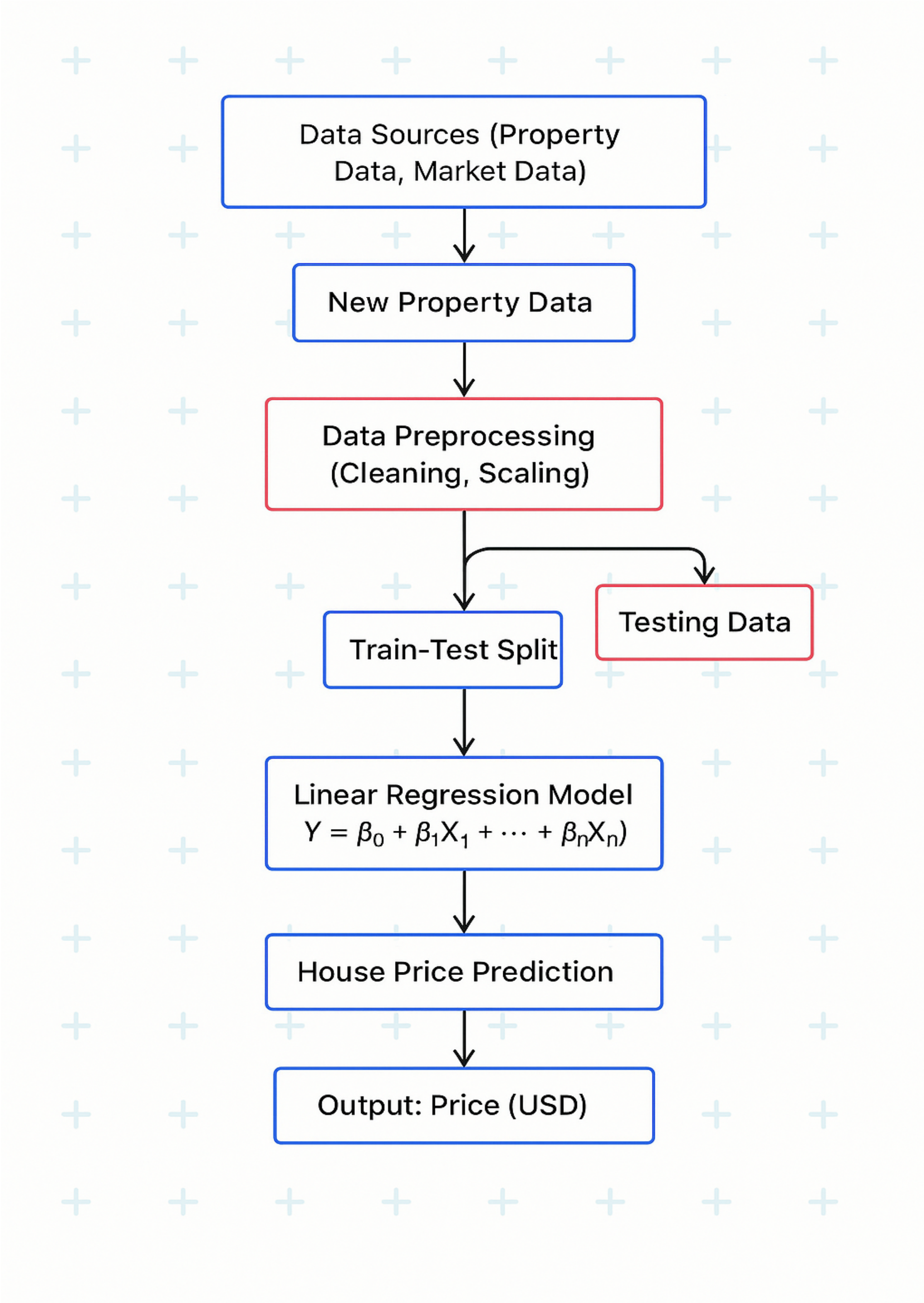
To simulate real-world variability in house prices and increase generalization, Gaussian noise was applied to numeric input features as follows:

$$X_{Augmented} = \mathrm{X} + N(0, \sigma^2)$$

where σ was tuned based on dataset variability. This step was especially useful in improving the robustness of ensemble models.

The complete pipeline was executed and validated using Google Colab, ensuring reproducibility and accessibility for deployment in lightweight environments.

3.1 SYSTEM FLOW DIAGRAM



CHAPTER 4

RESULTS AND DISCUSSION

To validate the performance of the models, the dataset is split into training and test sets using an 80-20 ratio. Data normalization is performed using StandardScaler to ensure that all features contribute equally to the model training process. Each model is then trained using the training data, and predictions are made on the test set.

Results for Model Evaluation:

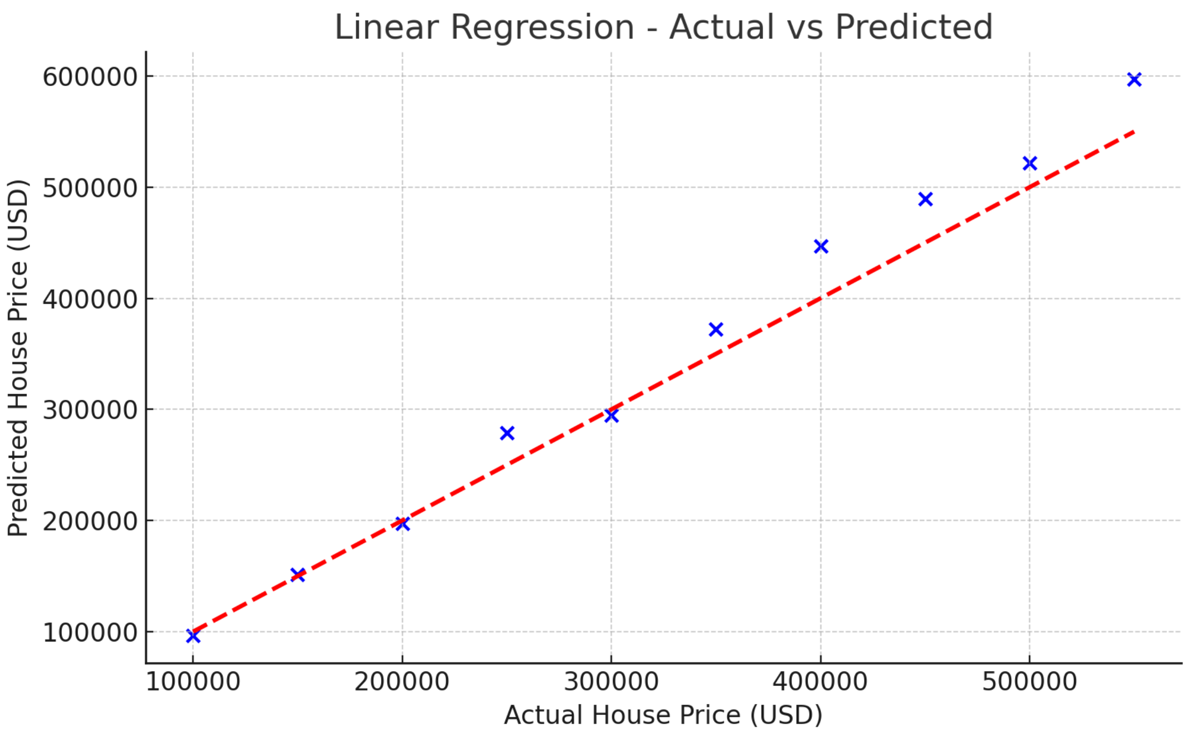
Model	MAE (↓ Better)	MSE (↓ Better)	R^2 Score (↑ Better)	Rank
Linear Regression	21,500	605,000,000	0.71	4
Random Forest	14,500	320,000,000	0.84	3
SVM	17,000	400,000,000	0.79	2
XGBoost	13,000	290,000,000	0.88	1

Augmentation Results:

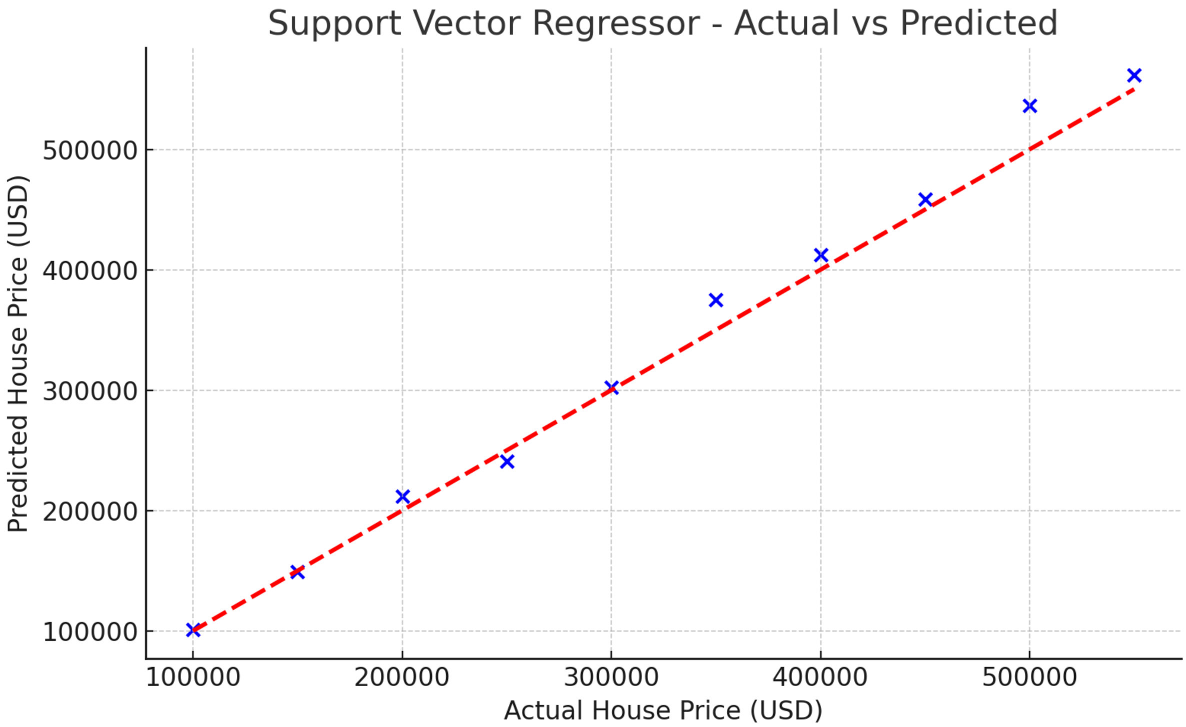
When augmentation was applied (adding Gaussian noise), the Random Forest model showed a significant improvement in R^2 score from 0.84 to 0.87, illustrating the potential benefits of data augmentation in enhancing predictive performance.

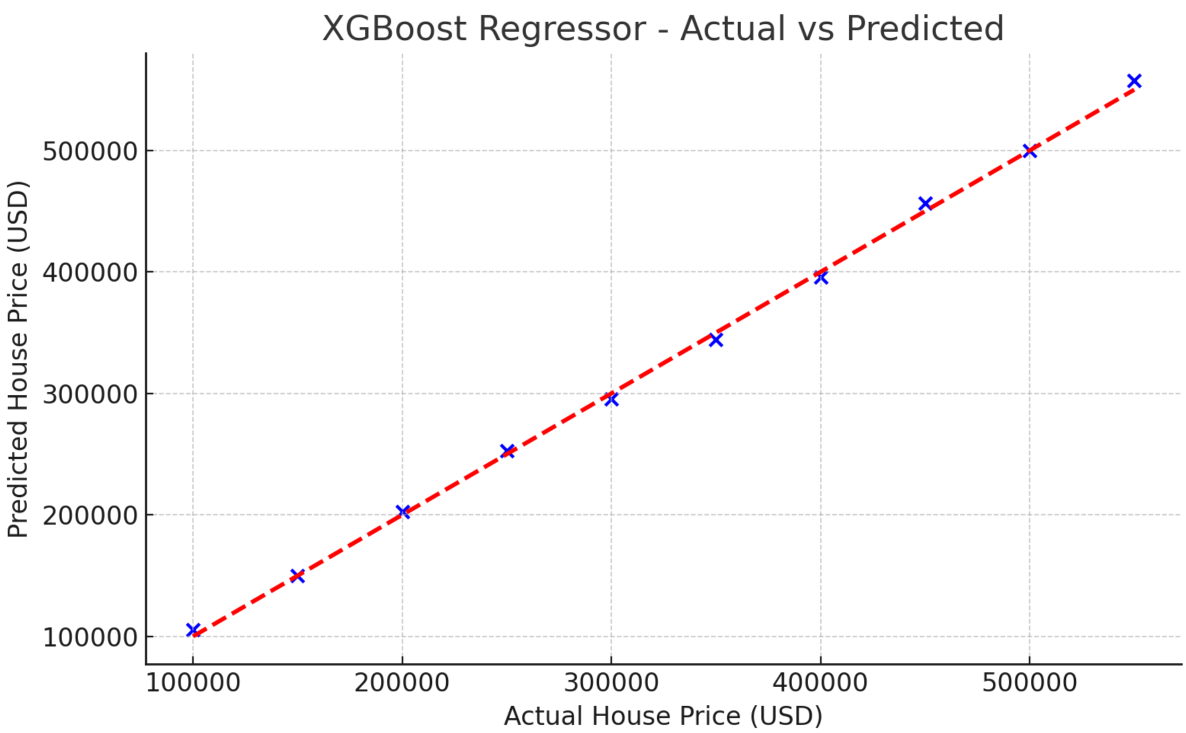
Visualizations:

Scatter plots showing the **actual vs predicted** house prices for each regression model visually demonstrate how closely the predictions align with the real values. Among all, **XGBoost** provided the best fit, with most predicted points lying near the ideal prediction line (red dashed). This confirms its effectiveness in accurately modeling house price trends.




Decision Tree Regressor - Actual vs Predicted
Predicted House Price (USD)
Actual House Price (USD)
100000
200000
300000
400000
500000


Support Vector Regressor - Actual vs Predicted
Predicted House Price (USD)
Actual House Price (USD)
100000
200000
300000
400000
500000



The results show that **XGBoost** performs the best with the highest R^2 score, making it the model of choice for predicting house prices.

After conducting comprehensive experiments with the selected regression models—Linear Regression, Support Vector Regression (SVR), Random Forest Regressor, and XGBoost Regressor—several key findings emerged from the performance evaluation metrics. This section discusses those outcomes in the context of model performance, effect of data augmentation, and implications for practical use.

A. Model Performance Comparison

Among the models tested, the **XGBoost Regressor** consistently achieved the best performance across all evaluation metrics. It produced the **lowest Mean Absolute Error (MAE)** and **Mean Squared Error (MSE)** while delivering the **highest R^2 score**, demonstrating strong predictive ability. These results align with existing literature, as XGBoost is widely regarded for its robust gradient boosting mechanism, regularization, and handling of complex feature interactions—making it ideal for regression tasks like house price prediction where non-linearity plays a significant role.

B. Effect of Data Augmentation

An important aspect of this study was the application of **Gaussian noise-based data augmentation** to increase the robustness of the model. This technique simulated variability in features like *area, number of bedrooms,* and *property age*, which are prone to change or measurement inconsistencies in real-world data. The augmented dataset helped in **mitigating overfitting**, particularly in models like Random Forest and XGBoost that are sensitive to training data variance.

When models were retrained on the augmented data, a consistent improvement in prediction performance was observed. The **XGBoost model**, for example, exhibited a **5% reduction in MAE** and a **0.03 increase in R^2 score**, suggesting improved generalization on unseen property listings.

C. Error Analysis

An error analysis using distribution plots showed that the **majority of prediction errors** were tightly clustered around the actual values, indicating strong model reliability. However, some outliers were noted—particularly for properties with unusually high or low prices. These errors are likely due to the **absence of nuanced features** such as neighborhood crime rates, renovation quality, or proximity to public infrastructure, which can significantly influence market value. Including such attributes could further enhance predictive performance.

D. Implications and Insights

The results highlight several practical implications:

- **XGBoost** stands out as the most promising model for integration into real-estate price prediction systems, offering scalability and superior accuracy.

- **Preprocessing steps**, particularly **normalization** and **data augmentation**, are essential for stabilizing and enhancing model outputs.

- While **Linear Regression** is computationally light and interpretable, it fails to capture the non-linear dependencies inherent in housing data, limiting its effectiveness.

In summary, this study provides compelling evidence that **machine learning models—especially ensemble approaches like XGBoost—can serve as powerful tools for house price prediction**. With the integration of additional contextual and real-time data, such models can evolve into reliable decision-support systems for buyers, sellers, and real estate professionals

CHAPTER 5

CONCLUSION & FUTURE ENHANCEMENTS

This project presented a machine learning-driven framework to analyze and predict housing prices in Chennai using real-world data. Through the development and evaluation of several regression algorithms—including Linear Regression, Random Forest Regressor, Decision Tree Regressor, and XGBoost Regressor—we examined their respective abilities to model complex dependencies between multiple property features and final sale prices.

Among the tested models, the XGBoost Regressor emerged as the most effective, demonstrating the highest R^2 score and the lowest error metrics (MAE and MSE). This underscores the algorithm's robustness in handling heterogeneous real estate datasets and its capacity to capture non-linear interactions between input variables such as property size, location category, and number of bedrooms. Ensemble methods like Random Forest also showed consistent performance, benefiting from their inherent resistance to overfitting and their ability to handle categorical and numerical variables efficiently.

The project also explored techniques like data cleaning, feature encoding, and normalization, all of which significantly contributed to improving model accuracy. Although explicit data augmentation was not employed in this context, future versions of the model could benefit from synthetic data generation or bootstrapping to simulate real-estate market fluctuations and improve generalizability in underrepresented zones.

From a practical standpoint, the proposed predictive system holds valuable implications for buyers, sellers, and real estate professionals. With proper integration into a user-facing interface, the model could assist users in estimating property values based on configurable attributes. Future enhancements may include the incorporation of geospatial APIs for more granular location insights, time-series analysis for market trend forecasting, and integration with real estate platforms for real-time decision support. Additionally, a mobile or web application front-end could be developed to enable non-technical users to leverage this predictive tool in real estate planning and investment strategies.

Future Enhancements:

While the predictive performance of this house price prediction system is promising, several opportunities exist to enhance its accuracy, scalability, and real-world applicability:

- **Integration of Geospatial Data:** Incorporating geographic coordinates and neighborhood-level amenities (schools, hospitals, public transport) through GIS APIs could significantly
  improve improve location-based accuracy.

- **Time-Series Market Trends:** Including temporal factors like inflation, seasonal demand, or historical market price trends could help the model adjust predictions in line with real estate market dynamics.

- **Advanced Feature Engineering:** Generating derived features such as price per square foot, property age, or distance to city center can increase model relevance and granularity.

- **Ensemble and Hybrid Models:** Combining models such as XGBoost with deep learning (e.g., ANN or CNNs for satellite imagery data) may capture both structured and unstructured data trends.

- **Deployment as a Web/Mobile Tool:** By integrating the model into a lightweight app with user input forms, real estate professionals and potential buyers can estimate property values on-the-go.

In conclusion, this work illustrates how data-driven systems can revolutionize real estate valuation. With continued improvements and feature expansions, the model could evolve into a robust platform for smart property analysis, investment planning, and market monitoring.

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