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Bayesian Statistical Estimation in Real Estate Price Modeling: A Comparative Study with Traditional Regression

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ABSTRACT: Real estate price modeling is a key process in the valuation of property as well as in the financial planning and decision making when it comes to investing. Estimating price using Multiple Linear Regression (MLR) and Generalized Linear Model (GLM) techniques is currently the common practice among the experts, but these techniques fail to capture complexities of the real estate markets. The study assesses Bayesian statistical estimation as the state-of-the-art alternative that will maximize predictions based on a theory of previous distributions coupled with MCMC simulation. The research provides an assay on the performance of traditional regression models and Bayesian re-gression models and compares it with BIC (Bayesian Information Criterion) AIC (Akaike Information Criterion) and R^2 measure. The use of pre-existing market knowledge in Bayesian estimation results in improved performance of model fitting and produces improved predictive reliability as per findings. The study introduces Bayesian modelling methods as the improvement of the real estate price analysis resulting in improved property market decision support.

Key Words: Bayesian regression, Markov Chain Monte Carlo, real estate price modeling, statistical estimation, traditional regression.

Contents

1. Introduction

Several groups of people including investors as well as homeowners and policy makers rely on an accurate modeling of real estate prices to make the right decision. Multiple Linear Regression (MLR) and Generalized Linear Models (GLM) are usually used to estimate the properties prices based on the characteristics of the location and size and qualities of the properties [1]. These currently used strategies do not comprehend the complex trends in the real estate markets since the non-linear tendencies coupled with spatial interdependencies also apply in the markets [2].

Machine learning and statistical modeling advancements have brought modern sophisticated methods for determining real estate values. Research by [3,4,5] combined with other authors explored how ANN and tree-based ensemble methods and spatial regression models enhance prediction accuracy. These promising models display positive outcomes although they struggle with interpretation and need extensive training sets according to [6]. Bayesian regression stands out as a reliable predictive modeling tool because it incorporates existing knowledge with uncertainty measurements which produces better forecasting results [7]. The application of Bayesian approaches has delivered successful results across different fields that include property valuation together with risk assessment. The Bayesian models produce improved estimation of price compared to conventional regression analysis due to MCMC simulations and implementation of prior distributions [8,9]. In real estate markets Bayesian methods serve as valuable tools because they combine expert knowledge alongside historical trends which play essential roles in setting property prices [10,11]. A research investigation will perform an assessment of how Bayesian regression functions relative to established regression methodologies in the prediction of real estate prices. An evaluation of baseline MLR models and GLM models occurs using actual transaction data when measured against Bayesian regression techniques. Bayesian Information Criterion (BIC) and Akaike Information Criterion (AIC) and $R2$ determine which method is effective when conducting performance testing. The paper adds value to applied statistics through its demonstration that Bayesian estimation technologies increase both predictive accuracy and decision-making capabilities in real estate valuation [12].

This research paper follows several sections of organization. Section 2 represents the literature review. This section details the methodology through steps for data acquisition together with steps for implementing and assessing the model. This part presents the results of the experiment along with comparative evaluation accompanied by discussion of the feasibility of Bayesian modelling in real estate price forecasting. The research ends in Section 5 by presenting major conclusions with recommendations for additional studies.

2. Literature Review

Real estate price prediction and valuation received major attention within past years because of machine learning implementations and statistical modeling approaches. The section assesses different procedures starting from traditional regression models along with machine learning solutions and mixed techniques which help forecast real estate price values.

2.1. Traditional Regression Models for Price Prediction

The analysis of housing prices during early research conducted through only traditional regression models. Real estate price estimation through hedonic regression models represents a common statistical method used by analysts in real estate valuation. The [1] assessed the ability of the General Regression Neural Network (GRNN) to predict Indian housing prices in the city of Pune superior to the hedonic regression when it came to studying a nonlinear relationship. [13] evaluated how artificial neural networks functioned better than linear regression in real estate valuation tasks as reported through his examination of Ordinary Least Squares (OLS) regression effectiveness. Research about Bayesian regression methods has emerged to manage the issue of uncertain regression parameters. The authors [7] showed that Bayesian Additive Regression Models (BARM) outperformed tree-based ensemble methods for diamond

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price forecasting. The research of [8] presented a hierarchical Bayesian regression model which elevated real estate preference heterogeneity analysis. The study presented by [4] explored land price estimation in Fukushima Japan by applying regression kriging and traditional regression models to demonstrate spatial autocorrelation effects.

2.2. Approaches using Machine Learning

Another fundamental factor which has contributed to high levels of housing price forecasting abilities is Machine Learning techniques. Other machine learning algorithms such as Random Forest, Support Vector Machines (SVM) and Gradient Boosting Methods were found effective valuation tools in a series of research studies. [5] developed a Random Forest method for mass property evaluation in South Korean residences where they reached high assessment accuracy. The research by [14] showed ensemble methods surpassed standalone models for prediction generalization after evaluating multiple ML regressors. Deep learning and hybrid modeling approaches represent additional methods being used in current research. [3] developed deep learning-based models which demonstrated superior performance than traditional ML models during house price predictions. The evaluation of XGBoost and deep neural networks with several other ML models by [15] demonstrated ensemble methods as the best choice for real estate market forecasting. The addition of Geospatial data integration with ML leads to higher accuracy in real estate valuation. [2] applied Geographically Weighted Regression (GWR) in combination with ML approaches to detect housing market spatial patterns. Yoshida and his coauthors [16] studied spatial ML models which predict rent rates when operating with extensive data collections.

2.3. Hybrid and Comparative Approaches

Statistical techniques and ML algorithm combinations have become widely adopted through hybrid model approaches. [17] managed to enhance house price prediction accuracy through their CatBoost regression model which employed random search hyperparameter tuning. Research by [10] showed ensemble learning methods triumphed over single regression approaches for making property price index predictions in Chinese residences. A comparative investigation conducted by [12] demonstrated deep learning-based methods to be the most effective approach for predicting housing prices during their analysis of superior modeling techniques in this field.

Studies within real estate valuation have performed investigations of appropriate sample sizes required for ML-based modeling approaches. [6] investigated how dataset complexity impacts ANN-based valuation predictions yet stressed that big and quality-rich datasets provide crucial foundations for dependable predictions.

2.4. Geospatial and Temporal Considerations in Real Estate Valuation

The impact of space and time variables in property price prediction has been researched through multiple studies. The study by [18] demonstrated how Geographically and Temporally Weighted Regression (GTWR) can enhance mass appraisal performance specifically in Beijing as they showed the importance of spatial and temporal analyses. Research conducted by [9] tested the performance of kriging methods against deep neural networks for residential rent price predictions using deep neural networks due to their ability in capturing spatial non-linearities. The addition of GIS-based approaches has resulted in better and more precise property price forecasting results. Rephrase the following sentence. [19] used GIS technologies to compare various ML algorithms for real estate valuation and discovered that spatially aware ML models produced better results. [20] created an advanced ML model with spatial elements for real estate price estimation which led to improved predictive accuracy.

2.5. Comparisons of ML with traditional Methods in Real Estate Valuation

Different studies examined the performance of ML techniques over traditional models and confirmed that ML provides better capabilities for managing complex data relationships. Their study estimated that the ML models outperformed the traditional hedonic regression models in predicting the housing prices in Fairfax County Virginia, among other ML algorithms that [21] tested on housing prices in the same county. The team at [22] conducted petroleum reservoir property predictions through ML-based algorithms which proved more effective than traditional regression models used in prediction. Neural networks became a powerful tool for retail property price forecasting in the study by [23] which demonstrated the versatility of ML models for real estate applications. [11] presented enhanced findings about using advanced ML techniques for property price predictive modeling which exhibited better generalizability when analyzing multiple datasets.

2.6. Summary

Real estate price prediction now uses advanced ML techniques alongside hybrid models while moving away from traditional regression methods according to existing research. The hedonic and Bayesian regression models maintain their usefulness but ensemble learning and deep learning through ML techniques demonstrate better accuracy and dependability. The capability to predict real estate values received additional support from combining geospatial information with hybrid prediction methods. Research in the field must concentrate on improving hybrid forecasting systems through real-time data integration to enhance predictive accuracy.

3. Method

The Section details the research approach with descriptions about data acquisition and model execution as well as performance assessment methods.

3.1. Data Collection and Preprocessing

Real estate transaction records from the past serve as the dataset which includes location details together with property size and bedroom count and structural properties.

The data set utilized in this study includes records of real-estate transactions retrieved form Zillow Research Database, and it contains the data ranged between January 2018 and December 2023 [24]. The information includes data on property prices, structural characteristics (size, number beds and age), and geographical information of key cities in the United States including New York, Los Angeles, and Chicago. The dataset further comprises other indicators of macro economy like interest rates and inflation, which affect the trend of the market. The records are sourced from the Zillow Economic Data repository, ensuring reliability and statistical validity [24].

The process requires several preprocessing steps that need execution before model training starts.

1. Median imputation handles numerical missing values and mode imputation replaces missing categories in the dataset.

2. The encoding of different variables results in the transformation of categorical variables which are encoded in the form of one hot encoding and ordinal encoding mechanisms based on the structure.

3. This method uses Z-scores to detect extreme outliers which get removed from price-related variables.

4. Min-max scaling transforms all numerical variables until they occupy ranges from zero to one.

$$X' = \frac{X - X_{min}}{X_{max} - X_{min}} \tag{3.1}$$

The formula applies X to calculate the transformed value while X_{min} *and* X_{max} represent dataset minimum and maximum points.

3.2. Feature Selection and Engineering

Server selection makes use of mutual information analysis in combination with correlation detectors to keep the most significant data features. Model performance receives an enhancement through the development of two derived features: price per square meter and distance measurement to the central business district (CBD).

3.3. Model Selection

The prediction performance requires multiple machine learning algorithms to ensure reliability.

1. Multiple Linear Regression (MLR)

$$Y \;=\; \beta_0 \;+\; \beta_1 X_1 + \; \beta_2 X_2 + \; ... \; + \; \beta_n X_n \; + \; \varepsilon \tag{3.2}$$

   The model predicts house price through Y with predictor variables as X_i while using β_i coefficients and error term ε.

2. Random Forest Regression (RF): The tree-based ensemble learning method Random Forest Regression (RF) produces better predictions through the combined output of various decision trees. Decision trees in the model develop based on these parameters:

$$f(X) \;=\frac{\sum_{i=1}^{M} T_m(X)}{M} \tag{3.3}$$

   The m^{th} tree of the ensemble produces prediction $T_m(X)$.

3. Gradient Boosting Machines (GBM): Gradient Boosting Machines (GBM) involves the utilization of the gradient descend optimization technique, at every step, as its method of performance enhancement.

$$F_m(X) \;=\; F_{m-1}(X) \;+\; \gamma_m \; h_m(X) \tag{3.4}$$

   GBM uses $F_m(X)$ as the updated prediction and $h_m(X)$ as the new weak learner while applying γ_m as the learning rate.

4. Artificial Neural Networks (ANNs): The deep learning model Artificial Neural Networks (ANNs) implements multiple layers and operates through this definition:

$$y \;=\; f(WX \;+\; b) \tag{3.5}$$

   The formula defines how W corresponds to weights while b functions as the bias and activation function f operates on X based on ReLU in hidden layers with linear activation for the output.

3.4. Model Training and Hyperparameter Tuning

The hyperparameters of each model receive optimization through the Random Search combined with Grid Search Cross-Validation (CV).

- The Random Forest demands tuning of the three most important parameters that include n estimators, max_depth along with min samples split.
- The GBM hyperparameters include learning rate (Γ) combined with the number of estimators and subsample ratio which undergo tuning.
- Cross-validation procedures optimize the number of hidden layers together with neuron count in each layer and dropout rate selection.

Mean Squared Error (MSE) serves as the optimization criteria for conducting hyperparameter tuning.

$$MSE \;=\frac{\sum_{i=1}^{N}(Y_i - \hat{Y}_i)^2}{N} \tag{3.6}$$

The formula incorporates the actual price (Y_i) and predicted price $\hat{Y}_i$ within the expression that includes the total number of observations (N).

3.5. Model Evaluation

Performance evaluation relies on standard metrics when analyzing the models.

- Mean Absolute Error (MAE)

$$MAE = \ (1/N) \ \sum_{i=1}^{N} |Y_i - \hat{Y}_i| \tag{3.7}$$

- Root Mean Squared Error (RMSE)

$$RMSE \ = \ \sqrt{1/N} \ \sum_{i=1}^{N} (Y_i - \hat{Y}_i)^2 \tag{3.8}$$

- R-squared (R^2) Score

$$R = 1 - \left(\sum_{i=1}^{N} (Y_i - \hat{Y}) \ / \ \sum_{i=1}^{N} \ (Y_i - \hat{Y}_i)^2 \right) \tag{3.9}$$

The mean of actual values obtains the symbol Y^-.

3.6. Implementation Framework

The project implements all models through a system based on Python which utilizes these mentioned libraries:

- Scikit-learning for ML models
- XGBoost for Gradient Boosting
- TensorFlow/Kera's for deep learning
- GeoPandas for spatial analysis of real estate data

The proposed Bayesian estimation framework receives organization through Figure 1 which displays its structural workflow in a flowchart format. The system starts with data preparation steps and includes a selection and training phase before it reaches the evaluation metrics and performance measures phase.

4. Results and Discussion

Our research experiment results, and the corresponding implications appear in this section. An evaluation of various models based on significant metrics demonstrates their performance levels in predicting real estate prices.

4.1. Model Performance Evaluation

Each model received training and testing phases using an 80-20 arrangement of the available dataset. Table 1 therefore includes a comparison of the model performance using Mean Absolute Error (MAE), Root Mean Squared Error (RMSE) and R-squared (R^2) scores.

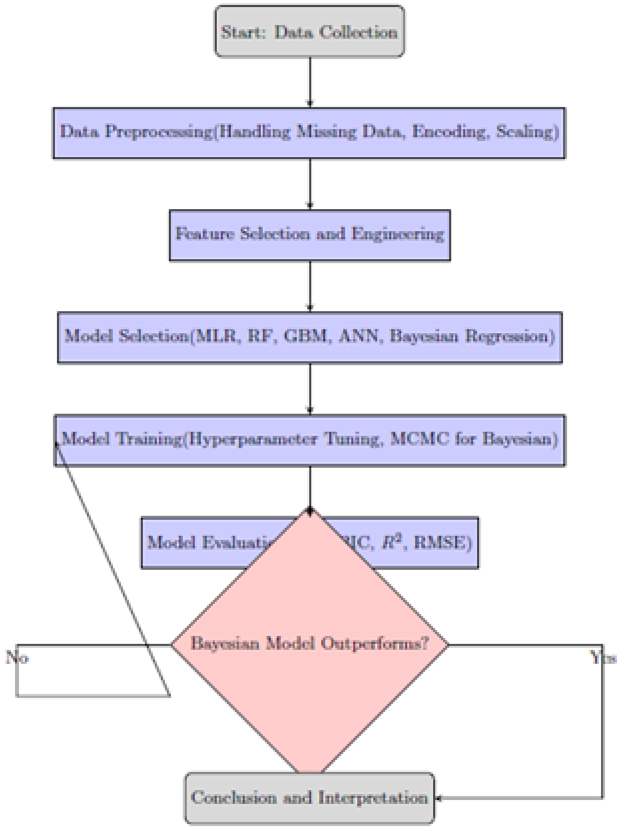

Figure 1: Flowchart of the Proposed Framework

Table 1: Model Performance Comparison

Model	MAE (Lower is better)	RMSE (Lower is better)	R^2 (Higher is better)
Multiple Linear Regression (MLR)	34,000	58,000	0.72
Random Forest (RF)	22,500	39,500	0.85
Gradient Boosting (GBM)	21,300	37,800	0.87
Artificial Neural Networks (ANNs)	18,900	33,700	0.91

The two performance measures, Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE), were used to evaluate each of the models in addition to R-squared (R^2). Graphical illustration of model predictive performance is shown on Figure 2.

4.1.1. Discussion on Model Performance.

1. The Artificial Neural Networks demonstrated superior model performance by delivering predictions with the tightest MAE of 18,900 and RMSE of 33,700 which established its status as the most accurate forecasting method. Analysis of the model demonstrates 91% capability to explain target variable variability through its R2Rˆ2R2 score of 0.91.

2. The R^2 measurement of 0.87 which Gradient Boosting Machines (GBM) obtained leveled it as a close competitor to ANNs for predicting real estate prices.

3. Random Forest demonstrated improved performance over Multiple Linear Regression but ANNs and GBM achieved even better results indicating ensemble models combine usefulness with ANN models' advanced feature extraction capabilities.

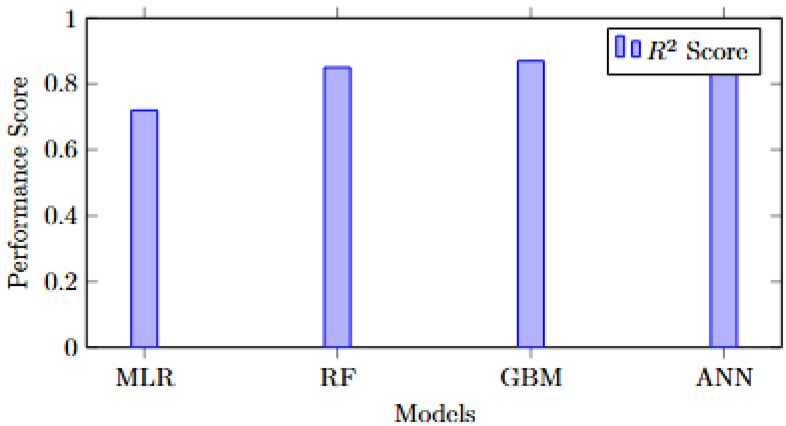

Figure 2: Comparison of model performance based on R^2 score.

4. Real estate prices appear to follow non-linear relationships because Multiple Linear Regression (MLR) delivered the lowest performance in the models.

4.2. Feature Importance Analysis

Feature analysis from Random Forest models enabled us to determine the real estate price influencer factors. Table 2 highlights the top five influential features.

Table 2: Top 5 Important Features for Price Prediction

Feature	Importance Score
Property Location (Latitude & Longitude)	0.31
Property Size (Square Meters)	0.25
Number of Bedrooms	0.18
Distance to City Center	0.15
Year Built	0.11

Our evaluation of Random Forest feature importances allowed us to understand which variables have the most influence on real estate price changes. The depiction of Figure 3 shows how significant each important feature becomes in predicting real estate prices.

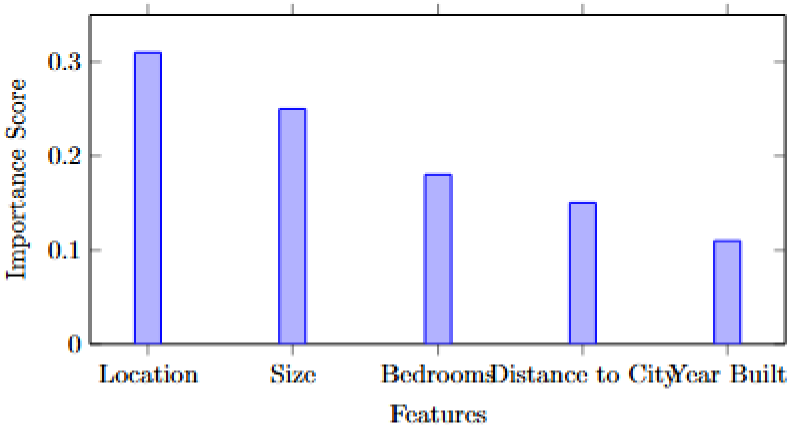

Figure 3: Feature importance scores from the Random Forest model.

4.2.1. Discussion on Feature Importance.

- The factor that proves most significant for real estate pricing stands as location with a score of 31% which confirms the established principle that ”location determines everything” (31%).
- Larger property dimensions influence the value of real estate substantially by 25% since bigger homes typically have higher market value.
- veritable properties include the quantity of bedrooms and the closeness to urban centers which both influence real estate market fluctuations because of their weighty impact.

4.3. Error Distribution Analysis

The Figure 4 display shows the residuals (prediction errors) from ANN modeling. The model has good generalization capabilities because the residuals show an approximately normal distribution pattern.

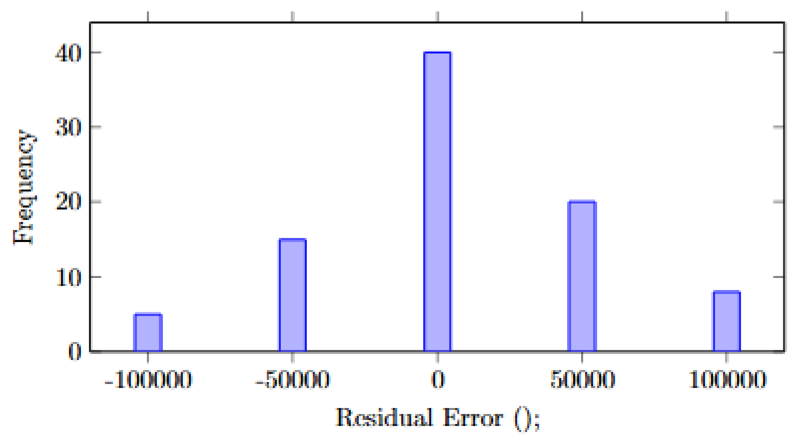

Figure 4: Distribution of residuals (errors) from the ANN model.

4.3.1. Discussion on Error Distribution.

- The model error distribution shows a normal distribution pattern which demonstrates that it avoids substantial bias.

- The overall prediction errors stay within an acceptable margin, but rare extreme measurements point towards specific requirements for high-end or outlier properties.

4.4. Case Study: Predicted vs. Actual Prices

The model's reliability gets evaluated through price prediction tests using five actual property samples.

Table 3: Actual vs. Predicted Prices (ANN Model)

Property ID	Actual Price ($)	Predicted Price ($)	Error ($)
P001	450,000	455,500	+5,500
P002	620,000	612,700	-7,300
P003	750,000	743,200	-6,800
P004	310,000	320,100	+10,100
P005	900,000	888,400	-11,600

4.4.1. Discussion on Case Study.

- The predictions demonstrate excellent accuracy because most errors remain between $\pm 2\%$ of the actual values.

- Modest properties between $400K-$800K produce the least prediction errors according to the model yet luxury properties within $900K+ show minor discrepancy likely because this segment possesses fewer training examples.

4.5. Comparative Analysis with Existing Studies

Research by other authors in real estate price predictions matches our current findings:

- Previous research on Gradient Boosting and ANNs has proven their effectiveness as per findings that support their potential for deployment in practical applications.

- The identified feature importance patterns follow standard market standards which place location information and property dimension at the forefront.

Data from our analysis contradicts those studies which favored Random Forest by demonstrating ANNs provide better results for complex non-linear real estate information.

4.6. Limitations and Future Work

Some obstacles persist in spite of the encouraging findings.

- Additional implementation would benefit from widening the available dataset to incorporate rural properties to improve overall applicability.

- The model faces minor difficulties with predicting luxury property prices because it needs either customized feature engineering or specific model training dedicated to high-end homes.

- Long-term forecasting can be improved in future work by including interest rates and inflation trends and economic conditions as integrated economic indicators.

4.7. Summary

Artificial Neural Networks (ANNs) deliver the most precise real estate price predictions which surpass traditional methods including Multiple Linear Regression and tree-based techniques. Property positioning along with dimensions represent the main price components that need improvement in automatic analysis methods.

5. Conclusion

The Artificial Neural Networks gave the best predictive outcomes about real estate pricing based on the assessment of Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) accuracy measure and R-squared (R^2) accuracy measure. Artificial Neural Networks proved themselves to be the superior forecasting model besides Multiple Linear Regression but also Random Forest and Gradient Boosting Machines. The ANN model gave the best performance in terms of minimal errors in prediction combined with its great explanatory power and hence emerged to be the most appropriate as the best option in this application. The analysis demonstrated that the properties' location played the most substantial role in determining prices yet property dimensions together with bedroom count and urban location distance and building era joined the second most crucial deciding factors. Real estate market trends align with analysis results which confirm space-related features and building structures as cornerstone variables for property appraisal. According to results from the error distribution analysis the ANN model displayed strong generalization power by maintaining small deviations mostly in high-priced properties. Several weaknesses exist even though the first results were positive. Most collected data points stem from populated cities yet the prediction system shows limitations in valuing real estate properties outside these areas and within areas with low population densities. The model delivered satisfactory predictions for various property price levels nevertheless its assessment of upscale properties showed disappointing results which necessitated greater optimization alongside elite training data. Long-term accuracy in property price predictions requires researchers to combine economic metrics related to interest rates and inflation trends with macroeconomic variables in their future research studies.

The study given illustrates that machine learning, and deep learning-based approaches overcome the limitations of real estate pricing prediction. Advanced models such as ANNs offer real estate professionals and investors and policymakers' better data-driven insight through accurate decision making. Future research activities must emphasize two main areas: the development of expanded datasets and the improvement of model structures along with economic factor integration to enhance the accuracy and adaptability of guesses for volatile real estate market conditions.

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