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REVIEWPAPER

# Trends, Challenges, and Future Directions in Machine Learning-Based Housing Price Prediction

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***Abstract*—Housing price prediction is a field that is of growing importance in research, given the economic implications of the field as well as the intrinsic complexity of the real estate markets. Conventional statistical and econometric approaches, e.g., linear regression and time series analysis, usually find it hard to reflect the nonlinear, multifactorial relationship that affects property values. With the rise of machine learning (ML) methods, predictive modeling has changed as now flexible methods that are data-oriented and can work with large and diverse datasets are possible. Decision trees and random forests, gradient boosting (XGBoost), and neural networks have proven to be more accurate predictors when compared to traditional models. The latest trends focus on ensemble and hybrid modeling, the incorporation of alternative sources of data, such as satellite imagery and socioeconomic factors, and the implementation of explainable AI (XAI) to promote transparency. Regardless of these developments, various challenges do exist, such as data quality, interpretation of the model, and dynamism of the housing markets. This paper presents an extensive literature analysis of the field of ML-based housing price prediction, including the attributes of properties that cause the greatest impact on their price, the methodological strategies that are pertinent, the current trends, and the principal limitations that limit the predictive accuracy, to provide an idea of the future studies and possible applications.**

***Keywords—Housing Price Prediction, Machine Learning, Ensemble Models, Deep Learning, Explainable AI, Real Estate Analytics, Predictive Modeling.***

## I. INTRODUCTION

Housing is an indispensable need of humanity, and food and water are also among the basic needs. During the years, housing demand has been increasing tremendously as the living standards have been elevated which has been an indicator of greater socioeconomic growth[1]. Whereas, some people buy property as an investment, majority buy houses as a source of living and housing. Housing markets are not only very important in the national economy but also vital to individuals in need[2][3]. The demand and supply of houses may have an impact on the currency and general economic stability of a country. By buying furniture and household products, homeowners can stimulate economic activity; contractors and builders can stimulate demand of raw resources and labor to initiate economic activity, and this has a cascading economic impact, commonly known as the housing multiplier[4]. A strong housing market does not only portray consumer wealth and investment ability but also portrays to a healthy construction industry which is crucial in terms of employment and development of infrastructure.

The conventional methods of housing price prediction have used statistical and econometric model, including linear regression and time series analysis. These are simple and interpretable methods that are frequently restricted in capability to grab the nonlinear, multifactorial, and intricate aspects of real estate markets[5][6]. The prices of houses would depend on a huge number of interconnected factors such as the location of the property, the features of its structure, the quality of the surrounding environment, the state of the economy, and time changes. Traditional methods are often unable to capture these interactions, especially in large data volumes, heterogeneous information or abrupt fluctuations in the market.

Machine learning (ML) offers more flexible data-driven modeling methods that are transforming predictive analytics in the housing markets by offering more flexibility. Nonlinear relationships are very complicated and can be learned using ML techniques, such as regression, decision trees, random forests, gradient boosting (XGBoost), and neural networks[7]. Such models have better predictive precision, capability to combine various features at the same time, and greater flexibility to dynamic market circumstances. Recent developments in ML-based housing price prediction also indicate the prevalence of ensemble and hybrid methods, deep-learning models, and incorporation of other types of data including satellite imagery, demographic data, social media sentiment, and data created by the IoT[8]. Parallel to that, automated feature engineering and explainable AI (XAI) have been getting more popular and allow users to gain greater insights into model predictions, create trust within the stakeholder, and comply with regulation frameworks.

### *A. Structure of the paper*

This paper reviews machine learning-based housing price prediction in following sections. Section II shows Attributes Affecting Housing Price categorizes locational, structural, and neighborhood factors. Section III talk about Challenges addresses data quality, model interpretability, and market complexity. Section IV presents Machine Learning Approaches. Section V shows trends highlights deep learning, AutoML, geospatial data integration, and XAI. Section VI shows compares recent studies, and Section VII summarizes insights and future research directions.

## II. ATTRIBUTES AFFECT HOUSING PRICE

House price prediction can be divided into two categories, first by focusing on house characteristics, and secondly by focusing on the model used in house price prediction. Many researchers have produced a house price prediction model, including. The attributes or factors affecting the house price differ for each house, therefore accepting the validity of this analysis as the main purpose of any research is to classify the factor or attributes affecting the house price. Various considerations influence the price of a house. The factors influencing house prices can be classified into three categories: location, structural and neighborhood condition.

### A. *Locational*

Location is considered to be the most significant feature of house price determination. In this [9] study also observed the significant of location attributes in deciding house price. The location of the property was classified in a fixed locational attribute. The close association between locational attributes such as distance from the closest shopping center, or position offering views of hills or shore, and house price variations.

### B. *Structural*

Another significant feature influencing the house price is structural structure or physical attributes. Structural characteristic is a feature that people may identify, whether number of bedrooms and bathrooms, or floor space, or garage and patio[10]. These structural attributes, often offered by house builders or developers to attract potential buyers, therefore meet the potential buyers' wishes.

### C. *Neighborhood*

Neighborhood qualities can be included in deciding house price. The efficiency of public education, community social status and proximity to shopping malls typically improve the worth of a property. There is a substantial rise in house prices from the fifth-class suburban community to affluent neighborhood as predicted.

### D. *Economic Growth*

Demand for housing is dependent upon income. With higher economic growth and rising incomes, people will be able to spend more on houses; this will increase demand and push up prices.

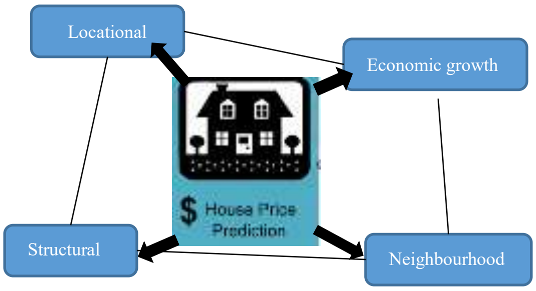


Fig. 1. Factors Influencing House Price Prediction

Figure 1 shows a detailed conceptual map on the house price prediction; the key determinants were divided into four dimensions. The fundamental topic of the analysis is the central goal to classify characteristics, which influence the value of property. They are the locational factors, which are commonly regarded as the most important characteristics and those include the distance to the shopping centers and scenic views. Structural features deal with the physical features such as floor space and bedrooms or bathrooms. As well, neighborhood characteristics, including social status of community and effectiveness of the education institutions of the locality, are crucial factors in establishing value. Lastly, economic growth is incorporated as a macro-factor, indicating that increased incomes lead to housing demand and consequently, increase the prices.

## III. Challenges in House Price Prediction

The inconsistency of data, the complexity of the model and multifactorial nature of the real estate market make it difficult to predict housing prices.

### A. *Data Quality*

The quality of the input data is highly relied upon in housing price prediction models. The lack of values, noisy data and outliers are all common problems that can produce undesired impacts on the model. The unobserved housing features can reduce the capacity of the model to reflect the property features whereas abnormal values that come about as a result of mistakes in data or abrupt market changes can taint forecasts[11].

### B. *Model Interpretability*

Most machine learning and deep learning systems are high-performance predictors but are black box, which are not very transparent. To the stakeholders including the home buyers, investors, as well as the policymakers, it is important to know how the predictions are produced to believe and apply them practically. This is because the un-interpretability may become a barrier to real-world usage and accuracy/explainability balance is important.

### C. *Market Complexity*

The price of a house depends on a variety of factors that are interrelated such as the location, economic conditions, development of the infrastructure, and time trends. It is not an easy task to capture such dynamic and complex relationships, and with the conditions in the market varying with time. Moreover, the accurate housing price prediction is further complicated by the choice of the relevant features when they are not introduced with bias and redundancy.

## IV. Machine Learning Approaches

Machine Learning (ML) algorithms refer to methods according to which artificial intelligence systems acquire patterns using data and give them output values in accordance with the input features[12]. Regression is one of the most important ML tasks as it is used to model the relationship between a dependent variable (y) and independent variable(s) (x). Regression aims at developing a mathematical formula that effectively approximates y based on the input features.

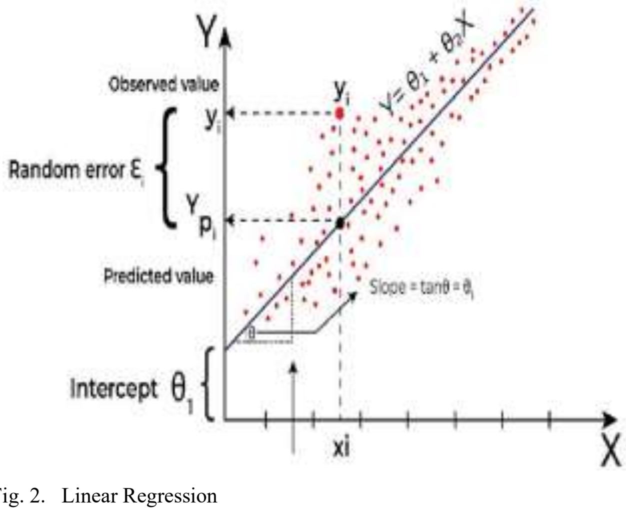


Fig. 2. Linear Regression

The most common regression method is the Linear Regression and is the simplest method of regression. It is easy to interpret and it models the linear relationship between dependent and independent variables. It is also well adapted to problems with linear relationship as it has a simple mathematical formulation, therefore it provides high speed of training and predicting[13]. The linear regression straight curve is presented in the Figure 2.

The Decision Tree Regression is the algorithm that employs the tree like structure to divide the data into smaller portions depending on the features values. To each internal node corresponds a decision rule whereas leaf nodes correspond to anticipated numeric values[14]. Decision trees are able to process numerical and categorical data and are easy to interpret, but they can have overfitting. The decision tree structure with decision makes by the nodes was presented in the Figure 3.

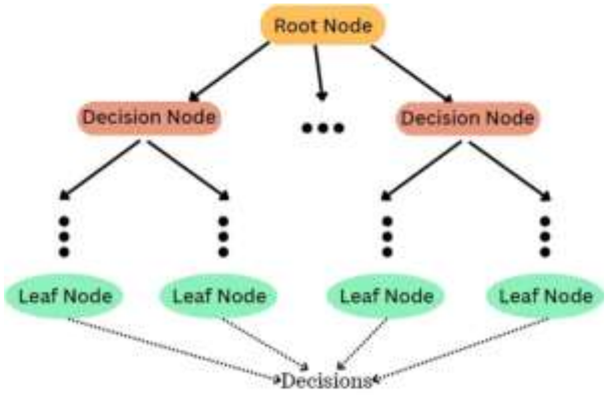


Fig. 3. Decision Tree

Support Vector Regression (SVR) uses the Support Vector Machine concepts on regression. It seeks to identify a function that does not coincide with actual target values within a value that is not larger than a given margin[15]. SVR is good at working with high-dimensional data and prevent overfitting; however, it is computationally costly and not as interpretable. The support vector machine structure is obtained in Figure 4.

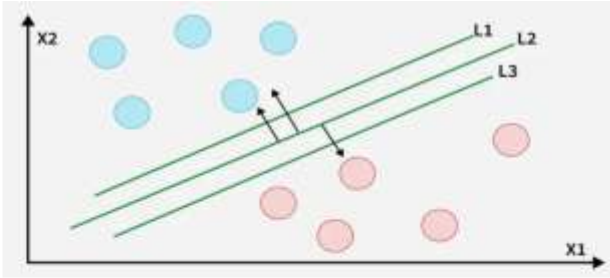


Fig. 4. Support Vector machine

Random Forest Regression is an ensemble regression algorithm which generates a number of decision trees concurrently with bootstrapped samples. An average of individual tree outputs is taken to obtain the final prediction. Random forests are more accurate, robust, and less prone to overfitting[16], but have lower interpretability and increased computing demands. The structure of a random forest is presented in the Figure 5.

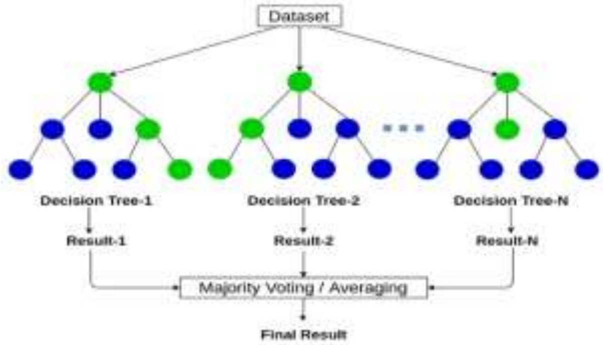


Fig. 5. Random Forest

The comparison Table I of four regression methods: Linear, Decision Tree, Support Vector, and Random Forest, by their features, drawbacks, speed of training and prediction, and understandability, shows the trade-offs between accuracy and simplicity.

TABLE I. COMPARISON OF MACHINE LEARNING TECHNIQUES

| Technique | Features | Disadvantages | Training Speed | Prediction Speed | Understandability |
|---|---|---|---|---|---|
| Linear Regression | Models linear relationships between dependent and independent variables; simple mathematical formula; works well for small datasets | Cannot capture complex non-linear relationships; sensitive to outliers; may underfit complex data | Very Fast | Very Fast | Very High; easy to interpret equations and results |
| Decision Tree Regression | Splits data into branches using feature values; handles numerical and categorical data; captures non-linear patterns | Prone to overfitting on small datasets; unstable with slight changes in data | Fast | Fast | High; intuitive tree structure shows decision rules clearly |
| Support Vector Regression (SVR) | Handles high-dimensional data; avoids overfitting; finds optimal function within margin of tolerance | Computationally intensive; complex parameter tuning; low interpretability | Slow | Moderate | Low; requires understanding of kernels and hyperparameters |
| Random Forest Regression | Ensemble of multiple decision trees; reduces overfitting; improves accuracy and robustness | Less interpretable; higher memory usage; slower with large datasets | Moderate to Slow | Moderate | Low to Moderate; multiple trees make explanation harder |

## V. TRENDS IN MACHINE LEARNING-BASED HOUSING PRICE PREDICTION

Recent housing price prediction dwells on the enhancement of accuracy, complex patterns and modification to changes.

- **Ensemble and Hybrid Modeling Approaches:** Ensemble methods, including Random Forests, Gradient Boosting, and XGBoost, are becoming more important in housing price prediction today[17]. These models can be used to predict better, minimize overfitting and serve a larger variety of patterns in housing data and do so by using a combination of multiple algorithms.
- **Deep Learning for Complex Pattern Recognition:** Neural networks and deep structure are currently being

implemented to capture non-linear dynamics and high dimensional interactions in housing markets. These models are especially useful in modeling spatial-temporal relationships.

- **Integration of Geospatial and Socioeconomic Data:** The use of GIS data, location of amenities, and other economic indicators in the area enable the models to contextualize the value of the property[18]. The trend can be used to explain the impact of location-based factors on pricing.
- **Explainable AI (XAI) for Transparency:** The stronger the complexity of predictive models, the more importance is paid [19]. Predictions can be made actionable because explainable AI methods assist the stakeholders in explaining model decisions, generating trust, and adhere to regulations.
- **Automated Machine Learning (AutoML) and Real-Time Adaptation:** Model selection is also being automated with the use of AutoML frameworks. Combined with the advantage of online learning and dynamism in the update of the dataset, models can change dynamically in accordance with the changing market conditions, producing timely and accurate predictions.

## VI. LITERATURE REVIEW

The literature points to the increasing use of machine learning in the prediction of housing prices, with a focus on model accuracy, importance of features, and insights based on data, although it discloses limitations in the interpretation, time dynamics.

Inmaculada Moreno-Foronda et al. (2025) article presents a systematic review analyzing studies that compare various machine learning (ML) tools with hedonic regression, aiming to assess whether real estate price predictions based on mathematical techniques and artificial intelligence enhance the accuracy of hedonic price models used for valuing residential properties. ML models (neural networks, decision trees, random forests, among others) provide high predictive capacity and greater explanatory power due to the better fit of their statistical measures. However, hedonic regression models, while less precise, are more robust, as they can identify the housing attributes that most influence price levels. These attributes include the property's location, its internal features, and the distance from the property to city centers[20].

Pita et al. (2025) analyzed research trends and identified research gaps in the field of ML applied to real state pricing. The results elucidated that the most frequently used models were Random Forest, Gradient Boosting Machine and XGBoost, Linear Regression, and Artificial Neural Networks. The "location", "condominium fee", and "property area" were the most employed features in each of the main categories: locational, financial, and physical, respectively. The main data sources for the ML models were real estate websites, which can present significant bias. A clear relationship was not observed between model quality metrics and the amount of data, nor the algorithm employed. The performance of the algorithms varied according to the database characteristics. The knowledge gaps identified are related to the impact of the time on property sale value, as well as the implementation of a correction factor that follows the sector's temporality and improves future predictions[21].

Mishra et al. (2024) consider multiple factors that influence house prices and strive to provide customers with successful predictions that align with their budgets and preferences. The proposed housing price prediction model employs AI algorithms such as Linear, Decision Tree, K-Means, and Random Forest Regression. The goal of this strategy is to eliminate the need for individuals to rely on intermediaries when making decisions on investments in real estate. The research findings highlight that Random Forest Regression offers the highest level of accuracy[22].

Sharma et al. (2024) assemble a large dataset of historical real estate transaction records that includes a wide range of property qualities, geographic data, economic indicators, and market trends. To ensure the data's quality and relevance, preprocess and sanitize it. In order to extract useful information from the dataset, feature engineering approaches are used. Exploratory data analysis (EDA) is then carried out to learn more about the distribution of the data and the relationships between the variables[23].

Gawade et al. (2023) article's goal is to make predictions about the coherence of non-housing prices. A crucial method to ease the challenging design is to use machine learning, which can intelligently optimize the best pipeline fit for a task or dataset. For individuals who will be residing in a home for an extended period of time but not permanently, it is essential to predict the selling price. Real estate forecasting is a crucial part of the industry. From historical real estate market data, the literature seeks to extract pertinent information. Land price bubbles grow as a result of real estate prices, which leads to macroeconomic instability. The government should look into the variables that drive up real estate prices so that it can use them as a guide to assist stabilize the area. There are many economic circumstances that are in play at the time also have an impact on the selling price of a home[24].

P et al. (2022) purpose of this article is to forecast the coherence of non-house prices. Using Machine Learning, which can intelligently optimize the optimum pipeline fit for a task or dataset, is a key technique to simplify the difficult design. Predicting the resale price of a house on a long-term temporary basis is vital, particularly for those who will be staying for a long time but not permanently. Forecasting house prices is an important aspect of real estate. The literature tries to extract relevant information from historical property market data. The price of real estate causes land price bubbles to expand, causing macroeconomic instability. The reasons that drive up real estate prices are important investigating so that the government may use them as a guide to help stabilize location, and various economic elements influencing at the time are all factors that influence the house selling price[25].

Table II represents a systematic review of previous research by area of interest, methodology, contributions, and limitations, illustrating the major gaps in the research concerning time modeling, data bias, interpretability and necessity of strong and hybrid forecasting models.

TABLE II. SUMMARY OF EXISTING STUDIES ON MACHINE LEARNING-BASED HOUSING PRICE PREDICTION

| Author(s) | Focus Area | Methodology | Key Contributions & Findings | Limitations & Future Work |
|---|---|---|---|---|
| Inmaculada Moreno- | Comparative analysis of ML | Systematic review of empirical studies using | ML models demonstrate higher predictive accuracy and stronger statistical fit, while | Lack of hybrid frameworks combining ML accuracy with hedonic |

 

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|---|---|---|---|---|
| Foronda et al. (2025) | models vs. hedonic regression | ML (ANN, DT, RF) and hedonic pricing models | hedonic models offer interpretability by identifying key price-driving attributes such as location, internal features, and distance to city centers | interpretability; limited discussion on model generalization across regions and temporal market changes |
| Pita et al. (2025) | Research trends and gaps in ML-based real estate pricing | Bibliometric and methodological review of ML-based housing price studies | Identifies dominant algorithms (RF, GBM, XGBoost, ANN) and key features (location, condominium fee, area); highlights reliance on online real estate platforms as data sources | Absence of temporal modeling and seasonality correction; data source bias; need for time-aware models and correction factors to improve long-term prediction reliability |
| Mishra et al. (2024) | AI-driven housing price prediction for consumer decision support | Supervised ML models including Linear Regression, Decision Tree, K-Means, and Random Forest | Demonstrates superior performance of Random Forest Regression and emphasizes disintermediation in real estate investment decisions | Limited dataset diversity and absence of external economic indicators; future work could explore deep learning and region-specific scalability |
| Sharma et al. (2024) | Data-driven housing price modeling pipeline | Large-scale dataset preprocessing, feature engineering, EDA, and ML-based prediction | Highlights importance of data quality, feature engineering, and exploratory analysis for improved predictive performance | Does not evaluate advanced ensemble or deep learning models; lacks comparative analysis across different market conditions and temporal splits |
| Gawade et al. (2023) | Economic and macro-level factors in real estate price prediction | ML-based predictive modeling using historical market and economic data | Emphasizes the role of economic variables in housing price fluctuations and links real estate prices to macroeconomic stability | Limited model interpretability and validation across different housing segments; future research needed on policy-aware and explainable ML models |
| P et al. (2022) | Long-term house resale price forecasting | Machine learning–based optimized prediction pipeline | Reinforces importance of ML in capturing complex price dynamics and highlights economic influences on housing prices | Lacks modern ensemble and deep learning approaches; minimal focus on temporal dynamics, data bias mitigation, and real-time market adaptability |

**Research Gap:** Although there has been an increasing use of machine learning in predictions of housing prices, there still exist a number of gaps. The majority of the studies pay more attention to the accuracy of the model and the selection of features, but do not consider the temporal dynamics, seasonality, and market cycles. Online real estate sources are associated with bias and restrict the scope of generalization. Hedonic regression models are interpretable and are not often combined with high-performing ML models. Also, macroeconomic, policy, and regional factors are not appropriately included. The study of hybrid frameworks, time-conscious models, and explainable AI frameworks to create a more robust, scalable, and practical applicability should be conducted in the future in various housing markets.

## VII. Conclusion & Future Work

Machine learning-based housing price forecasting is a strong and data-driven statistical alternative to conventional econometric housing price forecasting, which yields greater predictive accuracy and flexibility in response to non-linear and multifaceted market dynamics. The properties of the location, the structure, and the features of the neighborhood are considered to be the key influencing factors, and modern ML algorithms (Random Forest, XGBoost, and deep neural networks) allow modeling these multifactorial relations. Irrespective of these developments, problems of data quality, interpretability, temporal dynamics and model extrapolation across geographical area remain. Further studies are recommended to be done on hybrid architectures that are able to address the elements of ML accuracy with explainability, variety of data sources such as geospatial data, socioeconomic data, and IoT-generated data, and time-conscious correction factors in the dynamic markets. Predictive systems and AutoML pipelines can additionally be made real-time and more efficient in terms of models and deployment. Also, the implementation of Explainable AI (XAI) may lead to the establishment of stakeholder trust and regulatory adherence. By filling these gaps, more trustful, transparent, and scalable housing prediction models will be achieved, which will benefit investors, policymakers and consumers with their decision making.

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