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Using Machine Learning to Predict Housing Prices

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***Abstract*— Apartment prices are projected based on various apartment attributes such as location, square footage, population, latitude, and longitude. Real estate is generally seen as an investment vehicle for the modern consumer, which is reflected in the volatility of real estate prices and the impact of real estate markets on the global economy. A literature review is conducted to analyze relevant properties and the most efficient models for predicting property prices. The results of this paper demonstrate the effectiveness of machine learning techniques such as linear regression in predicting accurate prices. Our results also suggest that location and structural characteristics are important factors in predicting house prices. The study identifies key attributes used by property developers and researchers to determine property prices, and is particularly helpful in identifying the best machine learning models for conducting research in this area.**

Keywords*— *Property Prices, Prediction, Machine Learning, Real Estate, Linear Regression

I. Introduction

Apartment prices are projected based on various apartment attributes such as location, square footage, population, latitude, and longitude. Real estate is generally seen as an investment vehicle for the modern consumer, which is reflected in the volatility of real estate prices and the impact of real estate markets on the global economy. A literature review is conducted to analyze relevant properties and the most efficient models for predicting property prices. The results of this paper demonstrate the effectiveness of machine learning techniques such as linear regression in predicting accurate prices. Our results also suggest that location and structural characteristics are important factors in predicting house prices. The study identifies key attributes used by property developers and researchers to determine property prices, and is particularly helpful in identifying the best machine learning models for conducting research in this area.

Many international and human rights organizations stress the importance of living space. The house is a unit that is deeply ingrained within the socio-economic and socio-political fabric of a nation. However, it must be kept in mind that fluctuations in housing costs are usually a concern for homeowners. Local price spikes such as an increase in building and land costs can make homes unaffordable. Residents' quality of life and profitability are vulnerable to rising real estate prices, which may affect attractiveness as an investment opportunity.

Homes go up in price every 365 days, and house prices go up in a roundabout way every 12 months. Problems arise at the same time, as there are many variables that can affect property prices in addition to neighborhoods and property demand. Therefore, most stakeholders, including buyers and developers, property developers, and property companies, are willing to influence property prices to help buyers make choices and help developers set property prices.

Various learning models such as linear regression and artificial neural networks (ANN) are used in the prediction of real estate prices. Price prediction using such models provides many advantages to the various parties involved in the real estate market such as the buyers, the investors and the builders. The insights provided by this method are- Valuation of real estate prices in the current market, helping determine real estate prices. This model will also help potential buyers assess the home features they need within their budget. The insights provided by this method are- Valuation of real estate prices in the current market and helping determine real estate prices. This model will also assist interested parties in assessing the home features they need within their budget.

This is a report focusing on the prediction of real estate prices using machine learning models and an analysis of factors that influence housing costs. Following highlights the structuring of this report.

The first section summarizes this study as a whole. In the second section, we covered common attributes used to predict real estate prices around the world. Following this, we briefly discussed the machine learning models used to predict house prices in previous studies. The next section discusses the far-reaching impact of current property price forecasting models. Finally, Sections 5 and 6 provide a description and conclusions of this comprehensive literature review.

II. Factors

House price forecasts fall into two categories. The first focuses on residential real estate and the second on the version used to predict house prices. Many researchers have developed predictive models involving [1, 3, 6–8]. A study conducted by [9] uses conceptual models and questionnaires to analyze existing property prices in Jakarta, Indonesia. The attributes that have an effect on housing prices vary depending on the result. Since the data focuses on the residential projects in Jakarta hence the accuracy of the analysis is accepted as a given considering the fact that the primary focus of the study is to analyze the factors affecting property prices which are manifold. As inferred from [10], the factors or causes influencing house prices can be categorized into three types: neighborhood, characteristics, construction and location.

A. Neighborhood

Neighborhood characteristics, also known as geographic location, can influence home price decisions. According to [13], the quality of education, social status, importance of location, and proximity to important landmarks such as government buildings, monuments, offices, and shopping malls usually enhance the value of a property. From lower-class neighborhoods to gated, affluent communities, there is a notable increase in real estate prices, as predicted by algorithms [16]. However, research [13] has found that these qualities are more cultural rather than equally relevant to different cultures.

B. Structural

Another important characteristic that affects property prices is physical characteristics [10, 13]. Structural attributes are the features that a person can identify, from the bedroom to the bathroom. These aforementioned qualities are in line with what potential buyers may find attractive and are hence offered by builders to appeal to said buyers. According to [14], in their previous research, structural characteristics were the most important consideration when home seekers decided what to buy. Their previous study [15] found that all of these attributes were positively correlated with rising house prices [16].

C. Locational

Location is recognized as the most compelling attribute in determining property prices [6, 9-11]. [12] also examined the importance of location attributes in determining home cost in their study. Property locales are categorized as static location attributes. All analyzed studies affirm a close relationship existing between specific locational attributes such as distance from the nearest facilities like malls, hills and coast view. And variations in real estate prices.

III. Learning Models Analyzed

As explained in [20], methodologies for determining home values can be divided into two classes: conventional methods and advanced valuation methods. Artificial neural networks (ANNs), spatial analysis frameworks and hedonic pricing tools are advanced valuation methods. The model one chooses to predict house prices is very important as there is an incredibly large model variety. In this area of research, a very widely used model is the regression analysis model. Various studies, such as [3, 10, 21] have made use of the model. According to [7, 22, 23], another such commonly used model is the support vector regression (SVR) model.

A. Regression Analysis

1) Hedonic Price Model: There is a wide gap between the real estate and consumer markets when it comes to their nature. According to [13], the housing market is characterized by characteristics of resilience, flexibility, and spatial fixation. Therefore, to predict market differences to a fairly accurate degree, the hedonic approach is preferred. In his paper [24], he laid the foundation for his hedonic model in 1939, but this work did not become widespread until his early 1960s, two decades later. During the early 1930s, this model was used by Court to analyze the price and quality value of vehicles. Hedonics was defined by [25] as “the implied prices of the attributes revealed to economic agents from the observed prices of differentiated products and a particular set of those properties”. Years of research and progress later, the hedonic approach to real estate pricing research was applied and integrated into the general real estate sector research field by Rosen [3].

The philosophy employed by Rosen consists of two distinct phases. First phase involves a regression of the product price performed in order to calculate the total cost of the component from its attributes. The first stage determines the price scale of the commodity, but at this stage it is not possible to generate an inverse demand function. Therefore, the second stage of estimation identifies an inverse demand function that can be derived from the implicit price function of the first stage. Previously, there was a study comparing three of his commonly used methods for measuring house prices: the simple mean method, the hedonic model, and the matching approach. As a result, we find that two of his methods, the simple average method, and the matching method, are biased when applied to the housing market. Therefore, the hedonic model gives the best results compared to his two most found versions [3].

The hedonic pricing model is based on hedonic market theory. It is a statistic-based model that assumes that sum of all attributes of an asset it its value.

2) Multiple Linear Regression: This model establishes relationships between the various variables under study. Correlation coefficients or regression equations can be used to assess the correlation of variables [26]. There are models that can ascertain the most significant features in interpreting the dependent variable. Data on independent as well as dependent variables is collected for specific price forecasting by multiple regression. The relationship between dependent and independent variables is determined using multiple linear regression; its effectiveness is shown by [27]. [28] uses Multiple Regression Models to account for improvements in independent and dependent variables.

This model works by assigning housing price forecasts as independent variables and values such as house price, size, property type and bedrooms are assigned as dependent variables. Hence, house price is the target for the algorithm aka the dependent variables while the aforementioned influencing factors become assigned as independent variables. Thus, a correlation coefficient can be identified to determine the main variable.

B. Artificial Neural Network

The first example of an artificial neural network (ANN) was created in 1958 by [30]. Previously, in 1943, a paper titled "The Logical Computation of Ideas Immanent in Neural Activity" was published by Walter McCulloch. In this article, the structure and function of a biological neural network were used as a basis to artificially construct a neural network. Because this model often facilitates learning, other studies have argued that artificial neural networks are diagrams of artificial brains [31, 32].

An artificial neural network model was chosen whenever nonlinear attributes were involved. The spatial view of house prices is also non-linear, so the house price estimation analysis should also use this model. Therefore, their work, like [32-35], is expected to yield good results and provide accurate predictive models using artificial neural network algorithms. However, the performance of this system is very limited. House price prediction involves many nonlinear variables, so ANNs can model complex nonlinear relationships.

C. Support Vector Regression

The model bases itself on Support Vector Machines. SVMs, are tri-layered neural networks and are an incredibly effective supervised learning method. A subset of the training data is used to base a model off of it. This grants many advantages unique to support vector regression, such as its ability to handle non-linear results, its ability to provide a unique optimized result, and its ability to overcome the SSL problem [23]. The potential to generate market forecasts for multiple markets, which also consists of the housing market, shows that the problems of SSL and non-linear regression can be overcome using this model. Furthermore, the model is widely used in real estate pricing modeling [22] as it does not rely on probability distribution assumptions or the ability to map input attributes linearly or non-linearly. There are many advantages associated with support vector regression which exist in different fields as this model avoids over fitting problems while making sure that all structural and experiential risks are minimized, and an optimized solution is ensured [29].

D. *Gradient Boost*

Developed in 1999 by [36], Gradient boosting is a common machine learning algorithm recognized for its distinguishing qualities such as- consistency, performance, and interpretability. Gradient boosting is considered avant-garde in various machine learning activities, like B. In recent years, however, gradient boosting has been facing several challenges especially since the advent of Big Data. A major challenge is to strike a balance between accuracy and performance. A dynamic between regularity and fitness is ensured by using the following parameters: (1) adjust the regularization parameters (lambda, alpha) and (2) reduce the learning rate and to determine optimal parameters [19].

IV. Additional Investigation

The floor area of a house, as stated in [13], is the most important factor in determining real estate value as was corroborated in a previous screening of 14 articles that was conducted to the same end. However, according to research, adding 100 square meters to the house increases the value of the house by 2.6%. They also concluded that reducing a building's operational life by one year, he said, would increase the building's value by 0.3%. House prices also increase by 10.4%, and 13.7% for each additional bedroom or bathroom.

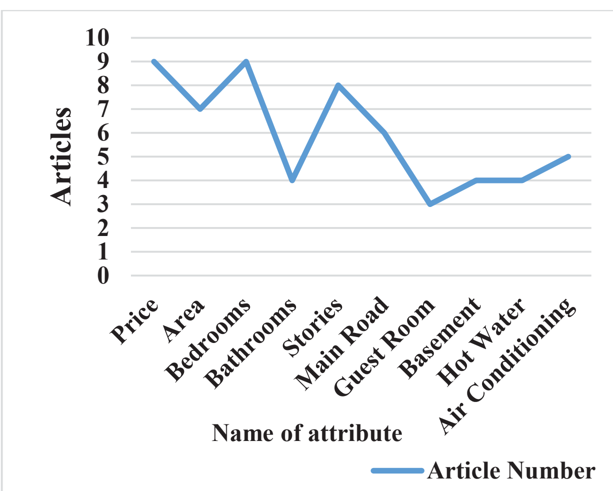

Fig. 1. Attributes analyzed in previous studies.

Previous peer-reviewed research has shown that 19 attributes are commonly used by other researchers to assess real estate prices. The 10 attributes shown in Figure 1 are grouped and summarized in a chart. Hence it becomes easy to determine which attributes have been used by researchers to determine house prices. Numbers in the top bar graph represent cumulative papers using attributes as predictors.

According to the given chart, site size, access to hospitals, shopping centers and such are the main properties used to ascertain prices. Recent research has been dominated by discussions about location attributes.

In fact, [16] states that location is an important predictor of house prices. As expected, the location attribute's contribution to real estate prices fell from the top group to his fifth place. [5] points out that his four objects that have had the greatest impact on real estate prices are locational attributes such as campuses, amusement parks, schools and hospitals.

In contrast, eight out of his 14 studies used the following structural characteristics to determine property prices: This result is consistent with [7] who found a significant association between the number of bedrooms and bathrooms and house price. Similarly, [17] found that additional floors, bedrooms, and washrooms increase house prices by 13%, 16%, and 2%, respectively.

In addition to structure and location attributes, neighborhood attributes are used by many researchers to determine real estate value. [12] argues that neighborhood influences affect housing prices significantly. Low crime rates, a quiet atmosphere, and pleasant landscaping are understood to be important neighborhood attributes. The value of a property is influenced significantly by these factors.

Few researchers have emphasized economic characteristics, such as personal income and home construction costs, as factors in determining house prices, but it is generally agreed upon that economic factors play a huge role in impacting house prices. [9] shows in his research that house prices may be based on the earning of an individual, as governments play a role in setting house prices according to an individual's financial situation. [12] endorses the study, noting that the affordability of a property is determined by the relationship between the value of a house and the income of the individual. This is one of the factors that make owning or renting a home affordable for everyone. Assessing key attributes that influence real estate prices is important and relevant to the first question of this research study.

After assessing key attributes that influence home price decisions, data mining techniques (predictive models in the context of this study) can be used to estimate home prices. Predictive modeling techniques such as SVR and ANN can be used to generate an estimation of property prices. Figure 2 shows the types of predictive models used by researchers in previous studies.

Artificial Neural Networks, Auxiliary Vector Regression, Multiple Linear Regression and classification are the four classifiers which the researchers have used to create this model.

In the study by [38], XG Boost is chosen as the best model because, in contrast to other models, XG Boost provides the lowest RMSE value. The second topic of research in this study is used is related to the aforementioned analysis.

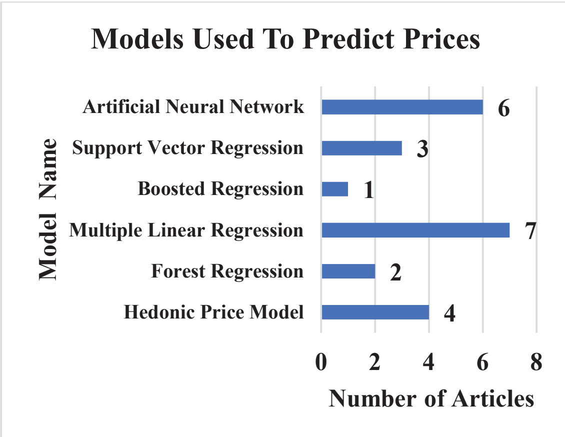

Fig. 2. Comparison of various predictive models used in past studies.

The impact of various attributes on the models under study was made easier to analyze thanks to attribute classification. An analysis of previous studies shows that support vector regression has the lowest RMSE value of 0.0047. Technically, the model's RMSE value is highly dependent on the attributes used during the forecasting process. Most of the models using the same attribute (location attribute) have very low RMSE values, indicating they are the best models. However, this alone does not indicate the best model. This is because some previous studies have provided few RMSE values to justify that the model is the best fit. However, it is to be noted that the RMSE values are very low when only the location attributes are present, but when the structural attributes are combined with the input location attributes for prediction, the RMSE values are very high.

V. Findings And Further Discussion

In this segment, the researchers have examined a relationship between property prices and the different predictive models. Additionally, the impact of different attributes on the studied models was also closely studied.

Based on reviews of numerous publications, it is ascertained that there are four key attributes that researchers use to predict property prices: structure, neighborhood, location, and economic attributes. The location attribute is composed of variables that quantify qualities such as accessibility to schools, access to hospitals, access to shopping centers, public transportation availability, and restaurants. Structural features, on the other hand, consist of variables such as number of bedrooms, number of bathrooms, living space, garages and terraces, age of dwelling, size of lot. Neighborhood is a highly subjective attribute that encapsulates socioeconomic factors such as scenery, quality of residents, crime rate, places of worship, quiet atmosphere, etc.. Finally, economic characteristics consist of an income factor and a material cost factor. Locational attributes as well as construction factors were the most common attributes used for the study, other attributes such as economics and regional characteristics are more difficult to determine and measure reliably.

ANN then returns the second lowest RMSE value of 0.0581. The results showed that the location attribute is the relevant attribute used in the ANN model to predict house prices. As was the case with SVR, structure and location attributes together yield very high RMSE values hence it is determined that the location attribute should be used alone in order to achieve low RMSE values when compared to the ANN model. Meanwhile, the XGBoost model yields the lowest RMSE value out of all even when the structural attribute was used alone. However, studies on models using only structural attributes are very limited. This is because previous research has focused primarily on location attributes, or a combination of location and structure attributes, to predict property prices. Generally speaking, the study has determined that XG Boost, ANN and SVR are the most efficient models for the task when compared to other models. The location attribute is the dominant attribute in predicting real estate prices.

VI. Conclusions

Extensive research was done on the various factors affecting housing prices and the intrinsic characteristics associated with an ideal house. Along with this various data mining techniques were analyzed and used to predict house prices. It was found that having access to strategic locations like shopping malls, hospitals, schools, etc. is one of the most important factors making such places more expensive than the countryside.

Accurate forecasting models help investors and homebuyers determine realistic home prices, and help developers determine affordable home prices. This paper focused on the attributes that previous researchers have used to predict house prices using various forecasting models. After various comparisons and analysis the results have clarified that XGBoost, ANN and SVR are the most efficient models in predicting real estate prices. These models work on multiple attributes as input and have a very low RMSE value when determining the predicted price. Thus the development of this model based on the aforementioned techniques is expected to have a very positive impact on the field of study and prediction of real estate value. In summary, the implications of this study should help and encourage other researchers to develop real-world models that can predict house prices easily and accurately which would, at the end of the day, further empower the consumer as well as the investor in making informed decisions regarding such huge endeavors like real estate investment.

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