PROJECT SYNOPSIS

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TITLE OF THE PROJECT:

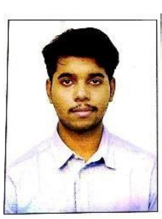
HOUSING PRICE PREDICTION USING MACHINE LEARNING

PROJECT GUIDE:

Ms. Sapna Juneja

1. INTRODUCTION:

1.1 AUTHORS



Harshil Prakash is pursuing his BTech degree of Computer Science for 2023 from KIET Group of Institutions.

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1.2 PROJECT

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 stay. House is deeply rooted in the economy, economy and political structure of each country. However, keep in mind that fluctuations in housing costs are usually a concern for homeowners, buildings and land, and local price spikes 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.

House price prediction can be done using multiple machine learning modes such as linear regression and artificial neural networks. There are many benefits that buyers, real estate investors and builders can derive from this model. This model provides many insights for these clients, including: B. Valuation of real estate prices in the current market. Helps determine real estate prices. In the meantime, this model will help potential buyers assess the home features they need within their budget.

This article presents a literature review that focuses on predicting house prices based on machine learning models and analyzing properties that are primarily used in studies that affect house prices. The structure of this paper is as follows. 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.

2. RESEARCH METHODOLOGY:

2.1 RESEARCH PROBLEM

- An accurate prediction of housing prices is an invaluable tool for investors
- Current prediction methodologies are academic only
- This project explores the possibility of a commercial application.

2.2. NEED FOR THE STUDY

- 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.

2.3. RESEARCH METHODOLOGY

As explained in [20], methodologies for determining home values can be divided into two classes: conventional methods and advanced valuation methods. Hedonic pricing tools, artificial neural networks (ANNs), and spatial analysis frameworks are advanced scoring methods. The model you choose to predict house prices is very important as there are many different types of models available. One of the most commonly used models in this area of research is the regression analysis model, which is regularly used in many studies, including [3, 10, 21]. Another fairly popular model for predicting house prices is the support vector regression (SVR) model [7,22,23].

3. TOOLS / TECHNIQUES TO BE USED FOR DATA ANALYSIS:

A. Regression Analysis

i. Hedonic Price Model

The housing market is very different from the normal consumer market. According to [13], the housing market is characterized by characteristics of resilience, flexibility and spatial fixation. Therefore, the hedonic approach is preferred to accurately predict market differences. 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. In the early 1930s, Court used this model to analyze the price and quality value of vehicles. [25] defined hedonics 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". After many years of progress, Rosen has applied this approach to real estate price research and integrated it into the real estate sector research more generally [3].

Rosen's philosophy or model consists of two distinct phases. A regression of the product price on its attributes is first performed to calculate the total price of the component. 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 commonly found versions [3].

A hedonic pricing model based on hedonic market theory is a statistical model that assumes that the value of an asset is the sum of all its attributes.

ii. Multiple Linear Regression

Regression analysis is a model used to determine relationships between variables. Correlation coefficients or regression equations can be used to assess the correlation of variables [26]. Some regression models can determine which features are most important in explaining the dependent variable. Multiple regression analysis also enables specific price forecasting by collecting data on independent and dependent variables. [27] shows the effectiveness of multiple regression models in measuring the value of the relationship between dependent and independent variables. [28] Using Multiple Regression Models to Account for Improvements in Independent and Dependent Variables.

This model can be achieved by using house price forecasts as independent dependent variables such as house price, house size, property type, and number of bedrooms. So, set house price as the target or dependent variable, set the other attributes as independent variables, and identify the correlation coefficient for each attribute to determine the main variable.

B. Support Vector Regression

Support vector regression is a predictive model based on SVM. SVMs, which are neural networks typically composed of three layers, are a powerful form of supervised learning. A model is based on a subset of the training data. The advantages of support vector regression are its ability to handle non-linear results, its ability to provide only one possible optimal solution, and its ability to overcome the small-sample learning problem [23]. The potential to generate market forecasts for multiple markets, including real estate, shows that this model can overcome the problems of nonlinear regression and small sample learning. 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. Support vector regression offers significant advantages in so many aspects as this model avoids overfitting problems while ensuring a single optimal solution by minimizing structural and empirical risks provide [29].

This area of study uses support vector regression to gather details about neighborhood, structure, and location attributes.

C. Artificial neural Network

In 1958 [30] created an artificial neural network called ANN. Walter Pitts and Warren McCulloch published a paper in 1943 entitled "The Logical Computation of Ideas Immanent in Neural Activity". In this article, a neural network was artificially constructed based on the role and structure of biological neural networks. You said you can create. 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.

D. Gradient Boost

Gradient Boosting was developed by [36] in 1999 and is a commonly used machine learning algorithm due to its performance, consistency and interpretability. Gradient boosting provides state-of-the-art technology in various machine learning activities, such as B. multi-level classification, click prediction, and ranking. With the advent of big data in recent years, gradient boosting faces new challenges, especially regarding the balance between accuracy and performance [37]. Few gradient enhancement parameters. To ensure a dynamic balance between fitness and regularity, you can choose parameters as follows: (1) adjust the regularization parameters (lambda, alpha) and (2) reduce the learning rate and determine these optimal parameters again [19].

4. EXPECTED RESULTS OF THE STUDY:

We examined the relationship between house prices and predictive models included in this segment. In addition, the impact of various attributes on specific models was also evaluated and discussed.

Based on reviews of numerous publications, there are several attributes that researchers use to predict house prices. All of these attributes can be grouped into four main categories: location, structure, neighborhood, and economic attributes. The location attribute consists of variables that describe accessibility to shopping malls, accessibility to schools, access+91 91299 18417ibility to hospitals, restaurants, and public transportation availability. 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, on the other hand, represents socioeconomic variables, crime rates, places of worship, pleasant scenery, and quiet atmosphere, and variables are highly subjective. Finally, economic characteristics consist of an income factor and a material cost factor. The attributes most commonly used to predict house prices in previous studies were location and construction attributes. Regional and economic characteristics are difficult to define and measure.

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 with SVR, using the location and structure attributes together yields very high RMSE values. This indicates that the location attribute should be used alone to achieve low RMSE values from the ANN model. On the other hand, the XGBoost model has the lowest RMSE, even when only structural attributes are involved. 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. In general, our analysis suggests that SVR, ANN, and XGBoost are the most efficient models compared to other models, with the location attribute being the dominant attribute in predicting real estate prices.

5. LITERATURE REVIEW / RELATED RESEARCH OUTCOMES

Predicting Housing Sales in Turkey Using Arima, LSTM and Hybrid Models

(A.S Temür, M. Akgün and G. Temür)

https://www.researchgate.net/publication/334557537_Predicting_housing_sales_in_Turkey_using_ARIMA_LSTM_and_hybrid_models

A study done on housing sales in Turkey and a look into how housing companies determine how they would make sales the following year. A study of the various technologies used for making estimations was also done. The study did an analysis of a 10 year dataset from Turkey. A HYBRID (LTSM and ARIMA) model was used for the application. MAPE and MSE values were used for the comparison. It was concluded that the HYBRID model was most successful in predictions. This study is a pioneer study done in the field of housing prediction and the models developed proved to be incredibly useful to our own project which in turn will help obtain crucial information to support the decision making process of shareholders in the sector.

Housing finance inaccessibility for low-income earners in Malaysia: Factors and solutions

(A. Ebrkozien, A.R Abdul Aziz and M. Jafar)

https://www.mecs-press.org/ijmecs/ijmecs-v12-n6/v12n6-4.html

A study done on the various data mining techniques and the relevancy of data mining in extracting relevant information from raw data. The study analyzed Artificial Neural Network, Support Vector Regression and XGBoost among other models and determined them to be the most efficient. The study was incredibly helpful in exploring the various techniques used for scraping data. This is further explored within the contents of the paper itself.

Driving forces for the US residential housing price: a predictive analysis

(A. Jafari and R. Akhavian)

Built Environ. Proj. Asset Manag., vol. 9, no. 4, pp. 515–529, 2019, doi: 10.1108/BEPAM-07-2018-0100

Results show that the main driving force for housing transaction price in the USA is the square footage of the unit, followed by its location, and its number of bathrooms and bedrooms. The results also show that the impact of neighborhood characteristics (such as distance to open spaces and business centers) on the housing prices is not as strong as the impact of housing unit characteristics and location characteristics.

The developed framework which is capable of predicting the driving forces of housing prices and predict the market values based on those factors could be useful in the built environment and real estate decision-making processes. Researchers can also build upon the developed framework to develop more sophisticated predictive models that benefit from a more diverse set of factors.

Statistical Analysis of Housing Prices in Petaling

(Choong Wei Cheng)

University Tunku Abdul Rehman

An analysis of Petaling district in Malaysia and its sub regions by using a functional relationship model. A new linear functional relationship model was used for this analysis. A total of 41,750 records from November 2008 to February 2018 were analyzed in the study. 70% of the data was used as a training set for the model and the rest were used as a training set. The model nearly reached 40% predictions with <10% deviation. This study proved key in proving that strategic location is incredibly impactful in the pricing and value of a property compared to similar but less strategic locations. Further exploration is done within the paper itself.

Data-driven fuzzy rule extraction for housing price prediction in Malang, East Java

(R. E. Febrita, A.N. Alfiyatin, H. Taufiq and W.F Mahmudy)

2017 Int. Conf. Adv. Comput. Sci. Inf. Syst. ICACSIS 2017, vol. 2018-Janua, pp. 351–358, 2018, doi: 10.1109/ICACSIS.2017.8355058

Another study done on the fluctuations of housing prices in Indonesia due to an increasing demand in residential space due to rapid urbanization. This paper made use of Fuzzy inference systems. The research produces a fuzzy system with good interpretability to show a satisfactory result of its predictions. The paper provided another perspective to look into while exploring various techniques used in analysis fluctuations in house prices.

6. WORK DONE:-

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.

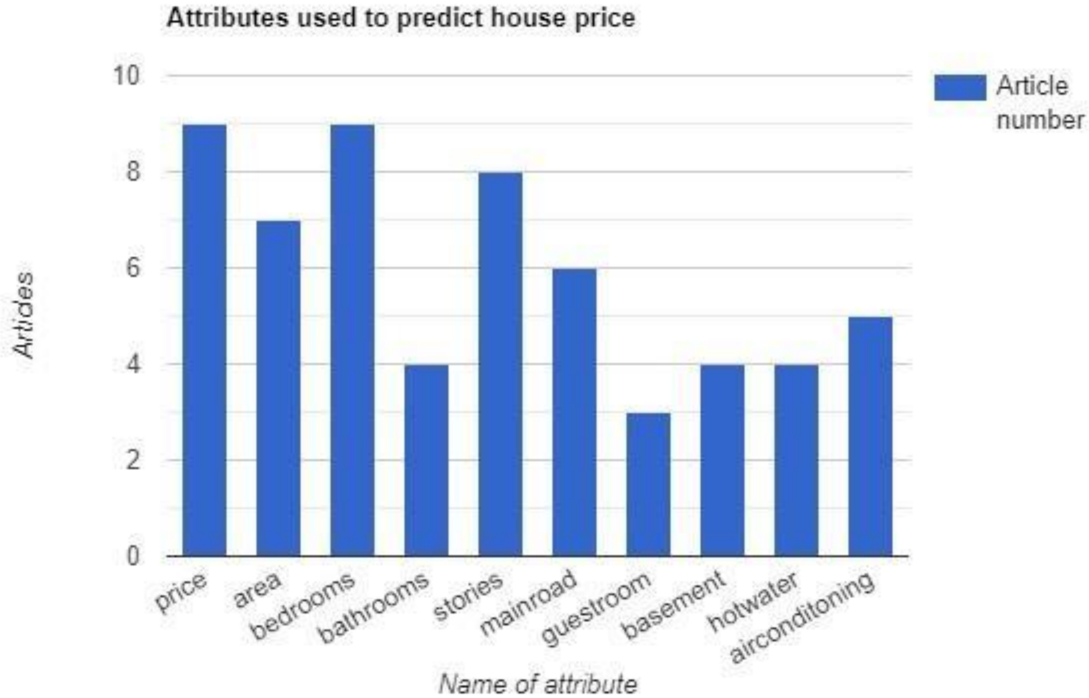

Fig.1. Attributes used in Previous Study

Previous peer-reviewed research has shown that 19 attributes are commonly used by other researchers to assess real estate prices. The 12 attributes shown in Figure 1 are grouped and summarized in a bar chart. So it's clear which attributes researchers have used extensively to determine house prices. Numbers in the top bar graph represent cumulative papers using attributes as predictors.

The chart above shows that access to shopping centers, hospitals, and site size are the main attributes used to determine property prices. Recent research has been dominated by discussions about location attributes, such as access to shopping malls and hospitals, and structural attributes, such as number of bedrooms and site size.

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 hospitals, schools, campuses, and amusement parks, which can be included in location attributes.

In contrast, eight 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 location and structure attributes, many researchers use neighborhood attributes to determine property prices. This can be seen in [12], arguing that neighborhood influences affect

house prices. Neighborhood attributes also include low crime rates, pleasant landscaping, and a quiet atmosphere. These factors determine whether real estate prices are high or low.
Few researchers have emphasized economic characteristics, such as personal income and home construction costs, as factors in determining house prices, but they agree that economic characteristics have a large impact on house prices. [9] His research shows that house prices may be based on an individual's income, as governments play a role in setting house prices according to an individual's financial situation. [12] He endorses the study, noting that the relationship between house prices and income is important in explaining housing affordability. 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 research question of this 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. We used predictive modeling such as support vector regression and artificial neural networks to predict house prices. Predictive modeling uses data mining to predict what she will observe during her studies. Figure 2 shows the types of predictive models used by researchers in previous studies. However, her

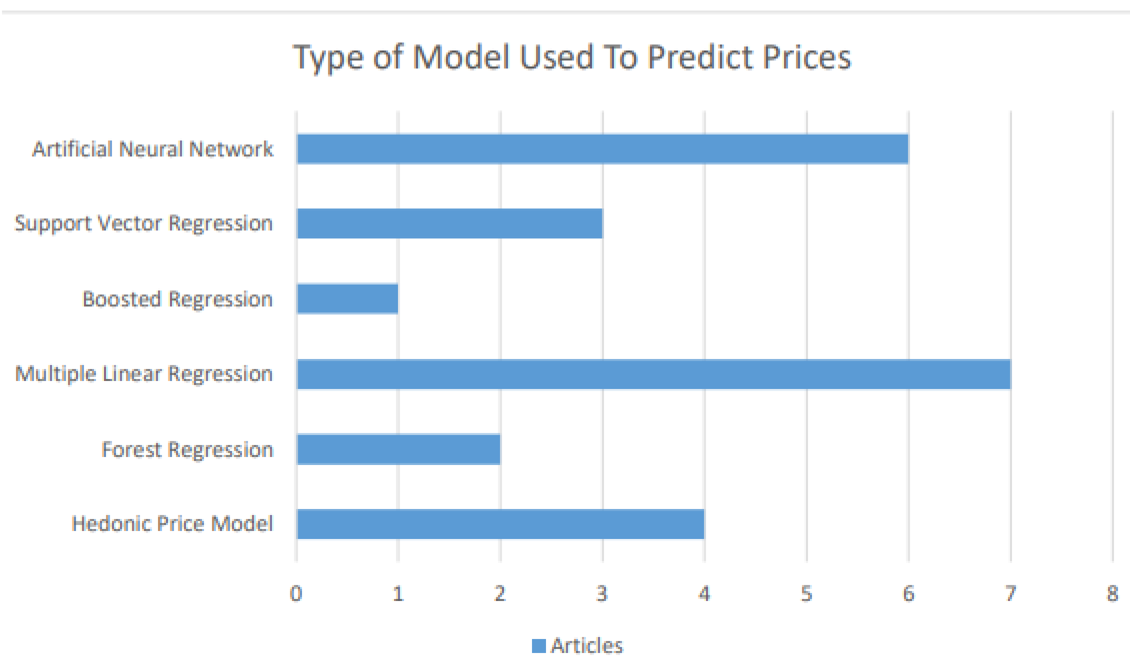

Fig 2. Types of Predictive Model compared in past Study.

four common predictive models (or known as classifiers) that researchers use to create this predictive model are multiple linear regression, auxiliary vector regression, artificial neural networks, and classification. It's a vessel gradient enhancer

In the study by [38], XGBoost is chosen as the best model because, in contrast to other models, XGBoost provides the lowest RMSE value. Such an analysis relates to his second research topic in this study.

Attribute classification made it easy to analyze the impact of different attributes on different models. A table of results based on analysis of previous studies is shown in Table 3. Looking at the table above, we can see that the 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. Based on the analysis table, we can assume that the location attribute is a key attribute used in several models such as: B. Support vector regression and artificial neural network support. 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.

7. CONCLUSION:-

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 analysed and used to predict house prices. It was found that access to strategic locations with access to facilities such as hospitals, shopping malls, good schools, etc were often more expensive than living in 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. Taken together, the results demonstrate the potential of SVR, ANN, and XGBoost in predicting house prices. These models are developed based on multiple input attributes and have a large positive effect on real estate prices. 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.

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