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Research article

Predicting Housing Prices in Riyadh: A Comparative Analysis on Machine Learning and Hedonic Regression

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ABSTRACT

This study investigates the performance of hedonic regression against artificial neural networks and random forest for real estate price prediction in Riyadh, Saudi Arabia. Using data from a major property platform collected in Q3 2024, the analysis spans 2,997 residential units across five major districts. The study is situated within the context of Vision 2030 and addresses the challenges of real estate valuations in a rapidly evolving urban environment. Twelve locational and structural features were analyzed using a 70/30 training-testing split. Random Forest led with test R^2=0.9065, RMSE=0.1911, MAE=0.1353, outperforming Artificial Neural Network (R^2=0.8968, RMSE=0.2008, MAE=0.1450) and Hedonic Regression (R^2=0.8034, RMSE=0.2673, MAE=0.1970). Random Forest feature importance: North of Riyadh (0.768659), West of Riyadh (0.612986), building type (0.180799), entrances (0.171134), size (0.127103). Random Forest and Artificial Neural Network excelled in capturing non-linear and spatial price trends in Riyadh's housing market. This study supports the incorporation of machine learning models into workflows for predicting property prices, especially in cities like Riyadh that are quickly urbanizing. The research provides a useful foundation for improving real estate valuation procedures in accordance with Saudi Arabia's Vision 2030 goals by demonstrating the predictive benefits of RF over conventional methods.

1. Introduction

Housing constitutes one of the primary human needs, and a substantial portion of household income is typically allocated to its purchase. As such, residential real estate is a critical asset class in household portfolios, and fluctuations in housing prices can have substantial macroeconomic repercussions [1,2]. Urban congestion and uneven development contribute to regional inflation in property markets, making housing price forecasting a valuable tool for planners and investors. This study investigates real estate price prediction in Riyadh, Saudi Arabia, within the context of urban growth, market complexity, and data-driven housing policy under Vision 2030. Saudi Arabia's urban housing market is undergoing rapid transformation, driven in part by strategic initiatives encapsulated in Vision 2030 the Kingdom's ambitious plan to diversify its economy and enhance quality of life. Vision 2030's housing related goals include expanding affordable housing supply, promoting private sector engagement, and improving urban infrastructure and governance. These reforms have crucial effects on market dynamics and housing prices, making accurate predictive modeling essential for policy and investment decisions.

In Riyadh, the capital of Saudi Arabia, rapid population growth, extensive infrastructure development, and shifting housing preferences have resulted in a highly segmented real estate market. The Kingdom's Vision 2030 initiative has further intensified housing market dynamics by encouraging private sector participation, modern urban planning, and enhanced home ownership [3]. Understanding price formation in such a rapidly evolving environment requires models that can handle nonlinearity, spatial diversity, and heterogeneous consumer preferences. The hedonic pricing method is a commonly used approach to estimate property values by decomposing price into the implicit value of its characteristics [4,5]. These characteristics are typically grouped into structural (e.g., size, age), locational (e.g., proximity to metro stations, CBDs), and environmental (e.g., views, air quality) factors. However, one challenge with hedonic regression lies in its reliance on linear or semi-log functional forms and pre-specified relationships between variables and price [2,6]. In practice, the relationship between housing features and value is often nonlinear and context dependent, particularly in complex urban markets like Riyadh. Several efforts have been made to address this limitation using advanced statistical techniques such as Box-Cox transformations and geographically weighted regression or semi-parametric models [7,8]. More recently, machine learning methods particularly artificial neural networks (ANN) and Random Forest (RF) have been deployed in real estate modeling for their ability to handle high dimensional nonlinear relationships without strict assumptions on functional form [9,10,11]. To address these challenges, this study compares conventional hedonic regression models against modern machine learning approaches Artificial Neural Networks (ANN) and Random Forests (RF) for price prediction of residential properties in Riyadh. Using a dataset of 2,997 residential units collected in Q3 2024 from a widely used real estate platform (Aqar), we apply cross-validation to optimize model parameters and assess performance using metrics such as Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and R-squared. By focusing on a localized dataset and comparing traditional and machine learning techniques. This study aims to provide actionable insights for urban economists, housing policymakers, and private sector developers in Saudi Arabia. The study aims to compare the predictive performance of hedonic regression, ANN, and RF for housing price prediction in Riyadh, providing insights for urban planners and policymakers under Vision 2030. The study was conducted using data collected from Riyadh, Saudi Arabia, in the third quarter of 2024.

1.1. Housing development and data issues

Cities have quite different housing markets in terms of pricing and geography. For instance, studies conducted in Western cities have demonstrated a pronounced pattern of segmentation brought about by economic and racial exclusion [12]. Apart from the ethical and political implications of these developments, a single property's value is constantly influenced by environmental, structural, and locational factors in its surrounding community [4]. While the adage "location, location, location" is crucial for assessing investment possibilities in the housing market [13], environmental and locational factors (such as the distance to the central business district [14] are sometimes more challenging to measure.

These foundational insights demonstrate the multifaceted influences shaping housing markets and underscore the critical role of location and urban amenities in determining property prices worldwide. However, contrasting dynamics emerge when we examine markets in different cultural and regional contexts.

Riyadh and other Saudi Arabian cities have their own sets of housing markets, more so depending on the area within that city and price range; the differences in these markets emanate from the peculiar cultural, economic, and social dynamics of the Kingdom. While Western cities may have housing market segmentation based on racial segregation and economic exclusion, in Saudi Arabia, the housing market characteristics are heavily based on the proximity to religious, commercial, and urban amenities. For example, the value of the property is highly affected by its closeness to areas such as mosques, shopping centers, and planned transport facilities.

Such localized factors, unique to Riyadh, influence spatial urban patterns and real estate valuation distinctly, highlighting the need for models sensitive to these socio-cultural and infrastructural determinants.

In Saudi Arabia, since the introduction of Vision 2030, several governmental reforms have been undertaken to tackle the housing problems, and a transition from a government allocated housing system to market forces has been provided. Given the Sakani programs, the opportunities for home ownership have opened for its citizens, thus changing the dimensions of urban housing. Housing in Saudi Arabia was once characterized by traditional neighborhoods where families lived close to essential services, like schools, retail outlets, and healthcare facilities. Development dependent factors, like public infrastructure and transit systems such as the Riyadh Metro, amongst others, have begun to shape the trajectory of housing values because of increased rapid urbanization. Similar to many other countries, housing units located close to urban centers, amenities, and transportation hubs are given fair value due to convenience. The property prices, in this case, gain an edge because of proximity to major transit hubs such as King Khalid International Airport and future Riyadh Metro stations, particularly in transit friendly developments. Indeed, considering the modern age demand exerted by the convenience of such access, the property markets of the suburban regions of Riyadh connected to the city via planned metro lines are gaining a higher premium. As in other cities, retail amenities in the form of shopping malls, supermarkets, and convenience stores, among others, are adding another dimension to increasing the value of properties. To understand the rudiments of the housing market dynamics in Saudi Arabia, it is important to understand how housing prices are affected by these amenities. The availability and granularity of urban data are crucial for undertaking efficient urban studies and real estate analysis, especially for Saudi Arabia. Data accessibility and transparency issues in the realm of property transactions pose further impediments to the study of housing trends. However, recent efforts to collect and categorize urban data regarding Points of Interest in Riyadh (such as schools, parks, and transportation nodes) create new opportunities for assessing the determinants of housing price and urban landscape change. This information is greatly needed by urban planners and policy makers aiming to develop fair housing policies in Saudi Arabia. With the help of advanced geospatial datasets and an accurate account of the factors affecting property values in Saudi cities, the future housing market study can contribute to urban planning and sustainable development.

1.2. Traditional hedonic pricing models

Research on property prices frequently uses the hedonic pricing model [4], rooted in consumer theory [15]. This theory suggests customers prioritize product features that meet their needs, with goods comprising various quantitative attributes. Residential assets are valued based on environmental, structural, and locational factors [16,17]. The hedonic model has been applied in housing research to assess nonabsorbable values of attributes like neighborhood amenities, air quality, airport noise, and commuter access (railway, subway, or highway). It is also widely used in environmental research, real estate pricing, and agricultural commodities assessment [18]. A key challenge for the hedonic model is spatial autocorrelation [19], which violates regression analysis's independence assumption, potentially causing biased estimates and low confidence levels [20]. To address this, two spatial autoregressive methods are proposed: the spatial lag model and the spatial error model [21,22]. In the regression $y = \alpha + \beta X + e$, the spatial error model accounts for autocorrelation in the error (e) component [17], while the spatial lag model addresses it in the dependent variable (y) [22,23]. However, these methods are rarely used for real estate valuation [24]. To handle spatial heterogeneity, Geographically Weighted Regression (GWR) approaches allow coefficients to vary by location [25,26]. According to Tobler's First Law of Geography [27], locally weighted linear regression can be applied, with coefficients reflecting nearby data points' influence. Brunsdon and Fotheringham [7] identified five GWR challenges, including variable selection and spatial autocorrelation. In Taipei, Peng and Chiang [28] used GWR to study geographical variations and public transportation's impact on property prices. Xiao *et al.* [29] developed a GWR model for Beijing's property market, outperforming Ordinary Least Squares (OLS) by raising R^2 from 0.56 to 0.79. Zhang [30] applied a mixed GWR technique for Nanjing's rent modeling, weighing some factors locally and others globally, achieving strong results. By incorporating non-Euclidean distance into GWR, Lu *et al*. [31] improved house price estimation in London, enhancing performance for proximity-based valuations. These advancements highlight GWR's potential in addressing spatial complexities in property valuation.

Although hedonic pricing models have been extensively used in real estate research, several studies have highlighted their limitations in capturing non-linear interactions and spatial dependence, which are often present in rapidly evolving urban environments. This recognition motivates the application of machine learning methods discussed below.

1.3. ANN

Borst [32] conducted one of the earliest applications of ANN on family home data sets in England. Tay and Ho (1992) evaluated how well the Multiple Regression Analysis (MRA) and back propagation neural network (BP) models performed in predicting home selling prices. Like the study by Tay and Ho. Nguyen and Al Cripps [33] compared ANN and MRA to forecast housing prices for single homes based on various data models, such as varying sample sizes, functional forms, and temporal prediction. Summaries of the performance outcomes of comparisons provide some information regarding the use of ANN and MRA. Limsombunchai and Samarasinghe [18] used a web database in Christchurch, New Zealand, to evaluate the predictive capabilities of an artificial neural network model with a hedonic regression model for predicting home prices. The study's findings recommended the usage of ANN by highlighting several remarks regarding its "black box" character and offering varying outcomes under various circumstances. Mousa and Saadeh [34] built an ANN model to automatically appraise Jordanian estates, avoiding the problems associated with manual evaluation by employing a genetic algorithm to determine the optimal network topology. A few statistical tests were conducted to verify the suggested approach's efficacy. Abidoye and Chan [10] utilized ANN to model property prices in Nigeria, they discovered that it may be a useful technique for obtaining accurate and dependable property valuations. Hasan Yıldırım [35] subjected the real estate data set from the Turkish province of Adana to hedonic regression, closest neighbors' regression, and artificial neural network techniques. The results show that, on all criteria, ANN performs better than the other approaches. Furthermore, even if the K-NN regression approach performs worse than the hedonic regression method, it still yields plausible findings. ANN is a potent instrument for forecasting home values. Chernyshova *et al*. [36] investigated supply demand relations to form predictions regarding real estate prices. The pricing of real estate is determined by socioeconomic factors, which create and sustain material factors. Lee *et al*. [37] developed their real estate index forecast model by comparing three different machine learning models and concluded that the random forest model made the most accurate predictions. Markey-Towler [38] built a short-term apartment pricing prediction model through machine learning technologies, based in part on the frequency with which keywords were searched for in news articles. They applied their model to a dataset provided by their research. A series of tests concluded that the model's predictive capacity was in line with expectations. Kang *et al*. [39] constructed a price prediction model for future auctions by integrating a regression model, an ANN, and a genetic algorithm using auction data from Seoul. The experiment's results allow the conclusion that separating the genetic algorithm based real estate auction prices prediction model into several sub-models, using the effective area of the auction appraisal price, leads to a higher gain in prediction accuracy. Elham Alzain *et al*. [3] goal is to use an ANN based prediction model to forecast Saudi Arabia's future home values. In Riyadh, Jeddah, Dammam, and Al-Khobar, four significant Saudi Arabian cities, the dataset was gathered from Aqar. The findings indicated that the experimental and projected values had a good degree of agreement. The employment of ANN in this results in an accuracy of 80%. Despite its global success, ANN's application in Saudi Arabia, particularly in Riyadh, remains limited, offering an opportunity to test its effectiveness in a market influenced by unique factors like Vision 2030 initiatives and cultural amenities such as proximity to mosques and other services.

ANNs are particularly suited for modeling the nonlinearities and interaction effects inherent in housing markets, outperforming traditional linear models in predictive tasks when carefully regularized to avoid overfitting [40].

1.4. Random forest

Several machine learning methods, such as logistic regression, random forests, voting classifiers, and XGBoost, were employed by Jha *et al*. [41] to address real estate market issues. To create an accurate property sales price prediction model that forecasted whether the negotiated sales price would be greater or lower than the advertised sales price, they integrated these algorithms with item coding. They assessed the model's accuracy, precision, findability, F1 rating, and error rate to gauge its performance. Out of the four machine learning algorithms that were examined, XGBoost outperformed the others and had the strongest model resilience. Three distinct machine learning techniques linear regression, decision trees, and random forest regression were examined by Adetunji *et al*. [42]. To get the best answers, their performances are compared and examined. While these approaches achieved the intended results, each model had advantages and disadvantages. According to experimental results, the suggested Convolutional Neural Networks (CNN) RF approach outperforms the other two methods; it performs very well on both training and testing data and has the lowest error. Three machine learning algorithms Support Vector Machine (SVM), RF, and Gradient Boosting Machine (GBM) were used by Ho *et al.* [11] to forecast real estate values. They trained these models on an 18-year data set of 40,000 real estate transactions in Hong Kong and compared the models' outputs. Three metrics MSE, RMSE, and Mean Absolute Percentage Error (MAPE) were used to assess the models' performance. Han Li [24] compared the performance of the Random Forest and XGBoost models to forecast property prices. In this research, two machine learning models are built, trained, and tested on the same dataset after missing values processing, correlation analysis, and sample standardization are completed on the original data. The study makes use of the Kaggle home price dataset ("House Prices Advanced Regression Techniques"). The collection includes 1420 samples with 79 attributes that cover nearly every aspect of a home. The findings demonstrate that the XGBoost algorithm achieves a higher R-squared score of 89%, suggesting that the XGBoost model can measure and predict house prices more accurately and efficiently.

Random Forest models combine multiple decision trees generated on bootstrapped training samples, thus reducing variance and improving generalization. RF models also provide interpretable metrics for feature importance, allowing analysts to assess the relative influence of housing attributes [43].

2. Material and methods

2.1. Hedonic regression model

"The weighing of the relative importance of various components among others in constructing an index of usefulness and desirability" [44] is the definition of the hedonic word, as previously noted. According to the hedonic price model, every feature of nonhomogeneous items offers a distinct profit or level of usefulness. The fair and realistic pricing of an item in its market is often ascertained using this approach. This strategy is based on the consumer theory that Lancaster [15] established, and Rosen [5] expanded to the real estate industry. The multiple regression model and the hedonic method serve the same functions. Regression analysis may make use of the hedonic idea. The price of a property is the dependent variable, while its qualities are the independent variable. In real estate and related markets, including the valuation of any item, regression analysis is referred to as the hedonic pricing model [20]. The hedonic analysis focuses on the relationship between a product's attributes and its price. Residential properties are rented or purchased because they provide utility or satisfaction from the amenities they have. Each home, whether it is an apartment, duplex, or house, has its features that affect its desirability. Structural attributes (land size, interior square footage, age of the building, layout of rooms, and additional facilities such as garages or air conditioning) are defined as structural. Locational aspects such as proximity to employment centers, retail stores, and recreational venues affect property values intrinsically. Environment and sociodemographic factors impact values because, through these two, the desirability of a neighborhood is defined. Similar forces affect how willing people are to pay for their housing unit. The most basic goal of hedonic analysis within real estate is essentially to quantify the relationship of structural and locational attributes to property prices. Observable, measurable items number of bedrooms, distance to school is certainly there, but not every factor observable through the lens is directly linked with price determination in the market. Through dynamics of supply and demand, the prices in the housing market act in their unique way, whereby their action on each unit depends upon a particular type of attribute and a more general market behavior, and therefore, the price of a housing unit is unique. Hedonic analysis aims to estimate the hedonic function, according to which each input attribute would set the market price. The hedonic analysis assumes that each characteristic of a property has its market, conditional on its supply and demand. Thus, every characteristic has its "hedonic price," which informs how much it contributes value to the property. Understanding this function is significant for three important reasons:

Property valuation: It facilitates the determination of the market price of a housing unit based on the attributes of that unit, thus contributing significantly to decisions in real estate appraisals and investment decisions.

Housing price indexing: Cost of living comparisons between regions are possible through price indices of constant quality. For instance, comparisons of housing prices in Riyadh and Jeddah will demand adjusting for differences across properties.

Policy analysis: Hedonic models provide a means to value certain implicit benefits from specific attributes, such as air quality, which improves insight into the social costs and benefits of environmental and infrastructural policies.

By using hedonic analysis, the construction of house price indices, which allow analysis for changes in market conditions while removing effects due to particular property attributes, is possible. In this study, hedonic regression is applied to estimate the implicit prices of housing attributes in Riyadh, identifying how structural and locational factors influence property values. To conduct the analysis, categorical variables were transformed into numerical variables, including Building Type (e.g., apartment, villa) and Location (North, South, West, East, Central Riyadh). In the hedonic regression analysis, dummy variable coding was employed, wherein East Riyadh served as the reference category for Location, while for Building Type, villas were set as the reference category. All categorical variables were one-hot encoded for binary input to the ANN, thereby ensuring compatibility with the input layer of the neural network. A product is sold as a collection of characteristics, which may be expressed in a matrix $f(x_1, x_2, x_3, \dots, x_n)$ [34]. This is the basic tenet of the hedonic pricing model. As a result, the product's market price may be represented as a function of these attributes, or $y = f(x_1, x_2, x_3, \dots, x_n)$. Equation (1) illustrates the hedonic pricing model's generic form:

$$y = \alpha + \beta \mathbf{X} + e, \tag{2.1}$$

where y is the price vector, e is the random error vector, α, β are the coefficient vectors, and X is the matrix of independent variables. Scholars have observed that heteroscedasticity can arise from a skewed distribution of both Y and x_n [30, 33]. Therefore, as the model was being implemented, we used the semi-log model.:

$$VALUE = e^{x\beta\varepsilon}. \tag{2.2}$$

Thus

$$ln\,VALUE = x\beta + \varepsilon. \tag{2.3}$$

In this case, the log of an item's expected price is the sum of its characteristics **X** times **β,** and the marginal price of each attribute x is:

$$PRICE\ (\boldsymbol{x}) = e^{xb}. \tag{2.4}$$

Where x is the current level of the characteristic and b is the regression coefficient. The marginal effect of an attribute in a semi-log model can be approximated as $(e^b - 1) \times 100\%$, representing the percentage change in price associated with a one-unit change in the characteristic. Notice that the semi-log form implies that the price of a given characteristic varies with its level, i.e., the prices are nonlinear. Compared to its linear version, the semi-log structural hedonic pricing model offers several benefits. It allows the value of one feature (like the number of bathrooms) to change proportionally with the value of other qualities (like the number of beds), which is its main advantage. A second bathroom offers the same value to a one-bedroom home as it does to a five-bedroom home, but this is not the case with a linear model. Also, given the skewed nature of housing prices, we apply a semi-log transformation to stabilize variance and improve interpretability.

2.2.ANN methodology

The computational and nonlinear statistical modeling technique known as ANN is based on human biological neurons [45,46]. Aerospace, automotive, banking, defense, electronics, entertainment, finance, insurance, manufacturing, medical, oil & gas, robots, speech, securities, telecommunications, and transportation are just a few of the industries that have made extensive use of it. In the context of regression, ANN may also produce precise predictions. One may think of it as a nonlinear regression technique [5]. Numerous sub-components, including weights, nodes, layers, and activation functions, make up a neural network structure. The input layer, which contains the values of the independent variables, the hidden layer, which has a specific number of processing units and nodes, and the output layer, which provides the estimated values of the dependent variable, are the three primary layers. Typically, weights are selected at random from a distribution of values within a predetermined range, such as [-1,1]. Utilizing total net, which is defined as the sum of weighted inputs and bias values, the last component, the activation function, generates values. There are connections between each of these elements. Similar to traditional regression models, it uses the same independent variables as inputs and the dependent variable as an output.

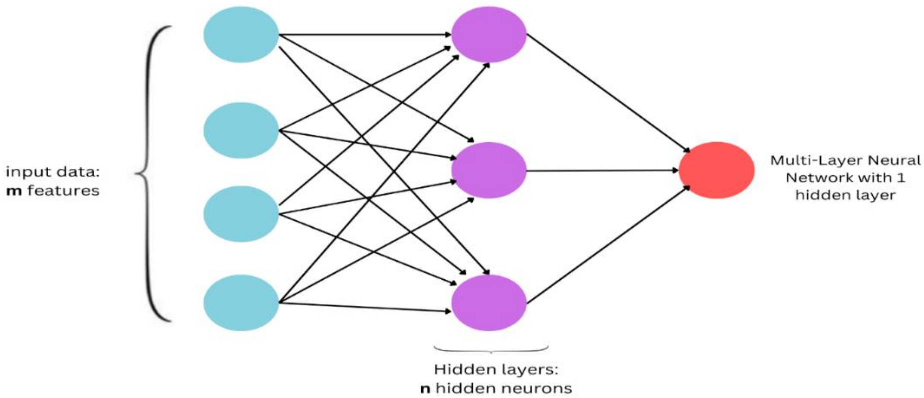

Figure 1: A sample structure of a multilayer neural network

To minimize the discrepancy between estimated and real dependent values, ANN essentially learns by analyzing the dataset itself and updating weights. Figure 1 illustrates a multilayer perception with one hidden layer, depicting the connections between input, hidden, and output layers. The input-hidden layer connection may be stated as follows and represented in linear form:

$$h_t(X) = g\left(W_0 + \sum_{i=1}^{P} X_i\, W_{it}\right), \tag{2.5}$$

where g(.) is the sigmoid activation function,

$$g\,(\,z\,) = \frac{1}{1+e^{-z}}. \tag{2.6}$$

The weight by w_{it}, and the bias value between each variable and the associated hidden node (t) by W_0. This value, $h_t(X)$, is only the result of the hidden node t. The result value may be similarly described as a linear combination of these nodes after the number of hidden nodes in the hidden layer has been determined [46]:

$$f(X) = \eta_0 + \sum_{t=1}^{M} \eta_t\, h_t. \tag{2.7}$$

In this case, the estimated result values are represented by $f(x)$. The sum of the squared residuals is minimized or reduced by updating the parameters of an ANN model. Several learning algorithms, including the popular backpropagation method put out by Kim and Nelson, are employed to carry out this updating process. Note that reaching the global optimal solution is not guaranteed [47]. In this study, ANN is used to complement hedonic regression by capturing nonlinear relationships and interactions between housing attributes in Riyadh. The ANN model employs a multilayer perceptron with one or two hidden layers, where the number of nodes per layer was optimized through 5-fold cross-validation. A sigmoid activation function is applied, and the model is trained using backpropagation with a learning rate of 0.01 for 500 epochs. Regularization techniques, including L2 regularization (λ = 0.01) and 20% dropout, were applied to the hidden layers to mitigate overfitting. Early stopping was implemented after 10 epochs without improvement in validation loss. Optimization of ANN architecture was carried out using 5 folds of cross-validation applied to a grid of one or two hidden layers with node counts {5, 10, 15, 20}. The smallest RMSE (0.2581) on the validation set was obtained with one hidden layer with 5 nodes and the second with 15 nodes. Alternative deeper architectures (ex., 3 layers) increased the complexity in computations (training time escalated from 2.3 to 4.1 min) but did little to enhance accuracy (RMSE=0.2592). To minimize the overfitting issue, L2 regularization (λ = 0.01) and 20% dropout rates have been used on hidden layers. From sensitivity tests with λ = {0.001, 0.1}, the decrease in RMSE was minimal (<0.002), while increasing dropout to 30% raised test RMSE to 0.2051. Hence, 20% became the optimal dropout rate. Early stoppage occurred after 10 epochs, where validation loss ceased to improve. This brought a gap in train and test R^2 that were previously 0.015 apart to just 0.0074.

2.3. RF methodology

A Random Forest is defined formally as follows: it is a classifier consisting of a collection of tree structured classifiers $\{h_k(x, T_k)\}, k = 1, 2, \dots, L$, Where T_k are independent identically distributed random samples, and each tree casts a unit vote for the most popular class at input x. As mentioned, RF employs the same method of bagging to produce random samples of training sets (bootstrap samples) for each random tree. Each new training set is built, with replacement, from the original training set. Thus, the tree is built using the new subset and a random attribute selection. The best split on the random attributes selected is used to split the node. The trees grown are not pruned. The use of the bagging method is justified for two reasons [47]: the use of bagging seems to enhance performance when random attributes are used; and bagging can be used to give ongoing estimates of the generalization error of the combined ensemble of trees, as well as estimates for strength and correlation. These estimates are performed out-of-bag. In a Random Forest, the out-of-bag method works as follows: given a specific training set T, generate bootstrap training sets T_k, construct classifiers $\{h_k(x, T_k)\}$ and let them vote to create the bagged classifier. For each (x, y) in the training set, aggregate the votes only over those classifiers for which T_k does not contain (x, y). This is the out-of-bag classifier. Then the out-of-bag estimate for the generalization error is the error rate of the out-of-bag classifier on the training set. The error of a forest depends on the strength of the individual trees in the forest and the correlation between any two trees in the forest. Strength can be interpreted as a measure of performance for each tree. Increasing the correlation increases the forest error rate, and increasing the strength of the individual trees decreases the forest error rate since a tree with a low error rate is a strong classifier. Reducing the number of random attributes selected reduces both the correlation and the strength [48]. The RF model used 500 trees having max depth=10, min samples split=5, min samples leaf=3 selected using the grid search over {100, 300, 500} trees and depth {5, 10, 15}. This setup was a tradeoff sweet in terms of accuracy (test RMSE = 0.1911) and overfitting (test-train RMSE gap = 0.0334 vs. 0.0451 for depth=15). ANN and RF techniques are selected among other models of Machine Learning for their capability of forecasting the nonlinear relationships and complex interactions due to the Vision 2030 project housing factors, which would include behavioral factors that influence the housing market of Riyadh. Unlike linear methods such as Lasso Regression, or simpler machine learning methods such as k-NN, ANN constructs feature hierarchies through the neural network multilayer perceptron and the RF, which is composed of 500 decision trees that smoothen the nonlinear thresholds using heterogeneous records (e.g., Size: 56-930 m²). These two have good robustness against mixed attribute datasets, but not SVM, which has multiple kernel tuning requirements. Their established effectiveness in real estate [11] and balance of predictive power (RF: test R^2 = 0.9065) with interpretability (RF feature importance) align with the study's benchmark goal using hedonic regression against Machine Learning (ML). Also, do not require much of the resource intensive alternatives (for example, deep learning), making them a perfect fit for this analysis.

2.4. Case study and data

The very highly renowned Riyadh, the capital city of Saudi Arabia, has long been recognized as the cultural, financial, and political hub of the country. The capital city has a population greater than 7 million people and is surrounded by the King Khalid Road, which outlines an urban area of about 1,500 square kilometers. Areas beyond this road were not included in the research as they are largely peripheral with limited support for urban functions. The main data has been retrieved from a well-known real estate website, Aqar (https://sa.aqar.fm/), during the third quarter of 2024 and georeferenced by property addresses. We collected 2,997 units and 12 variables, which are given with some descriptive statistics in Table 1. The dependent variable is listing price rather than transaction price, as actual transaction data are not publicly available in Saudi Arabia. Listing prices reflect seller expectations but remain highly correlated with transaction prices in this market, as noted in prior empirical work. The dataset belongs to five districts, including the North, South, West, East, and Center of Riyadh. The variables used are Building Type, Bedroom, Living Room, Bathroom, Kitchen, Size, Street Width, Floor, Age, Entrance Number, Elevator, and Location. The 2,997 units represent all available residential listings within Riyadh’s urban boundaries during the data collection period, with only properties having complete data for all 12 variables included. The variable “Location” is operationalized as a dummy variable for each of the five districts to account for spatial price variations. Key variables include Building Type (categorical, e.g., apartment, villa), Size (continuous, square meters), and Age (continuous, years), each expected to influence property prices based on their contribution to utility or desirability.

While actual transaction prices are preferable, they remain inaccessible in Saudi Arabia due to privacy regulations and limited public disclosure requirements. We rely on listing prices, which represent seller expectations and are publicly available through the Aqar platform. Research from comparable emerging markets suggests listing prices are highly correlated with transaction prices, particularly in regulated markets with standardized listing practices. In Saudi Arabia's context, the Aqar platform is the most widely used real estate marketplace, and listings undergo verification processes that reduce the likelihood of inflated expectations. Moreover, Vision 2030 initiatives have introduced greater transparency in the housing sector, narrowing the gap between listing and final transaction prices.

3. Results and findings

3.1.Data set and preprocessing

The issue of multicollinearity is significant due to the reference to near-linear dependences among independent variables. According to Montgomery [49], the presence of multicollinearity can result in unstable regression coefficients with high variances/covariances and absolute values. The condition index and variance inflation factor are used to assess the presence or absence of multicollinearity. The thresholds are set at 10 for the Variance Inflation Factor (VIF). These criteria show that there is no multicollinearity between independent variables. The outcome is shown in the hedonic result table. The dataset has been split into train and test data. Between them, with 70% for training and 30% for testing, respectively. Training data was used to fit the models, while testing data was used to evaluate them. RMSE, R-squared, and MAE have been computed and provided as performance metrics. The outcomes of hedonic regression analysis and artificial neural networks have been analyzed using Python 3.12 software. Which are presented in Table 1.

Table 1: Descriptive Statistics of Property Characteristics.

Variable	Min	Max	Mean	Std. Deviation
Bedrooms	1	26	4.19	1.78
Living Rooms	1	6	1.50	0.82
Bathrooms	1	8	3.32	1.11
Kitchens	1	6	1.04	0.29
Size (m^2)	56	930	199.44	114.05
Floor Number	0	10	1.57	0.88
Age (years)	0	20	2.48	3.99
Number of Entrances	1	2	1.02	0.32

In Table 1, the dataset's descriptive statistics are compiled. The figures show that most of the residences are apartments, which are typically smaller than villas and feature fewer bedrooms, living rooms, and bathrooms. Typically, apartments are 152.74 square feet in size, with 1–7 bedrooms, 1-3 living spaces, and 1–5 baths. On the other hand, villas are more expensive and diverse, with an average size of 347.13 square units, ranging from 2 to 26 bedrooms, 1-6 living rooms, and 1 to 8 bathrooms. The average size of a property is 199.44 square units, with 4.19 bedrooms, 1.50 living rooms, and 3.32 bathrooms, according to the total figures.

The dataset underwent rigorous quality control during data collection from the Aqar platform. Only properties with complete information for all 12 variables were included in the analysis, resulting in the final sample of 2,997 residential units. Properties with missing values in any field were excluded during the initial data cleaning phase.

Regarding outliers, descriptive statistics reveal property sizes ranging from 56 to 930 square meters, which represent legitimate market variations rather than data errors. The semi-log transformation applied to the dependent variable (housing prices) helped stabilize variance and mitigate the influence of extreme values without requiring arbitrary outlier removal. Additionally, the Variance Inflation Factor (VIF) analysis confirmed no multicollinearity issues (all VIF values below 4), and the Breusch-Pagan test ($p = 0.13$) confirmed homoscedasticity, indicating that the data structure was appropriate for modeling

3.2.Hedonic Regression Results

The hedonic regression results are given in Table 2. Which includes the hedonic coefficient, standard error, t-statistics, P-value, and VIF calculated below.

Table 2: Hedonic regression model result.

	B	Std. Error	t	Sig.	Tolerance	VIF
Building Type	-0.473	0.022	-21.673	0.000	0.275	3.642
Bed Room	0.012	0.004	2.837	0.005	0.447	2.24
Living Room	0.045	0.008	5.349	0.000	0.491	2.036
Bathroom	0.03	0.006	5.007	0.000	0.533	1.877
Kitchen	-0.005	0.019	-0.259	0.795	0.751	1.331
Size	0.002	0	27.336	0.000	0.36	2.775
Street Wide	0.001	0.001	1.468	0.142	0.821	1.217
Floor	-0.022	0.006	-3.599	0.000	0.815	1.228
Age	-0.007	0.001	-5.051	0.000	0.842	1.188
Entrance Number	0.047	0.016	2.972	0.003	0.942	1.062
Elevator	0.065	0.011	5.861	0.000	0.796	1.256
North of Riyadh	0.333	0.013	24.641	0.000	0.653	1.532
South of Riyadh	-0.686	0.016	-41.622	0.000	0.747	1.338
West of Riyadh	-0.298	0.013	-22.715	0.000	0.684	1.462
Central Riyadh	-0.169	0.045	-3.797	0.000	0.938	1.066
(Constant)	14.211	0.06	238.054	0.000		
F (P-Value)	840.452	(0.000)				

Categorical variables of hedonic regression results indicate a few key trends in the housing market of Riyadh. Deciding on physical characteristics and types of buildings is important, with apartments showing very low prices compared to villas (-0.473; $p < 0.001$). The number of bedrooms shows a mild positive effect on house prices, with each bedroom adding 1.2% to the price ($p = 0.005$). Where living spaces are concerned, the effect is larger, with each additional living space contributing 4.5% ($p < 0.001$) to the house price. Bathrooms are also positively affecting pricing; an additional bathroom will increase the value by 3% ($p <0.001$). Interestingly, despite its practical significance, the number of kitchens had an insignificant effect on pricing ($p = 0.795$). This may be because of the dataset's low variance (mean = 1.04, SD = 0.29) or Riyadh culture's preference for other features, such as location or size, over more kitchens. A more positive coefficient for property size is determined at least from the numerical values as one of significance (0.002, $p < 0.001$) - thus, higher prices are commanded for bigger properties. Street width has a positive trend but is statistically insignificant ($p=0.142$). Higher units would be less well priced, as their floor level adversely affects the price (-0.022, $p < 0.001$). Conversely, older units will expect a lower price because of the same negative parameter of the age (-0.007, $p < 0.001$) of the building. The number of entrances influences a positive price valuation on properties (0.047, $p = 0.003$), with the presence of an elevator increasing property values by 6.5% ($p < 0.001$). The location is thus a significant price driving factor for housing in Riyadh, with substantial distances between neighborhoods and East Riyadh (reference category). The properties in North Riyadh command a hefty premium, being priced 33.3% higher than East Riyadh ($p <0.001$). On the other hand, South Riyadh has the most negative effect, with the pricing 68.6% lower than the reference area ($p < 0.001$). Properties in West Riyadh are priced 29.8% lower ($p <0.001$), while Central Riyadh prices are 16.9% lower ($p <0.001$) in comparison with East Riyadh. Diagnostic tests for the model yielded strong results, with VIF values for all low predictor variables being below 4, implying that serious multicollinearity can be ruled out, while significance levels for most variables indicate the robustness of the model in explaining price variation in the Riyadh housing market. A Breusch-Pagan test ($p = 0.13$) confirmed no significant heteroscedasticity. VIF ranged from 1.062 to 3.642, with a condition index of 8.2, ruling out multicollinearity (Montgomery *et al.*, 2012). The regression model demonstrates strong statistical significance, with an F-statistic of 840.452 ($p < 0.001$), indicating that the predictors collectively explain a significant portion of the dependent variable's variance. Due to the absence of precise geographic coordinates (latitude and longitude) in the dataset, it was not possible to conduct explicit spatial autocorrelation tests such as Moran's I. Therefore, the study incorporates location dummy variables at the district level to partially account for spatial dependencies. This limitation suggests caution in interpreting results near district boundaries, where unmodeled spatial interactions may persist [22]. This constraint advises using caution when interpreting findings close to district boundaries, where unmodeled spatial effects may persist. To partially account for spatial heterogeneity, we employed district-level dummy variables (North, South, East, West, and Central Riyadh) in all three models. This approach captures broad locational premiums/discounts but has limitations at district boundaries where properties may share similar spatial characteristics despite being assigned to different administrative zones.

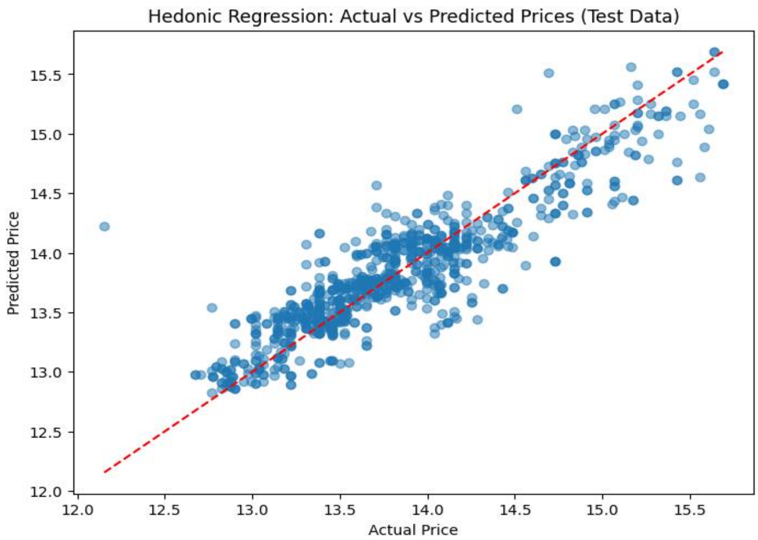

Figure 2: Observed and predicted house prices by hedonic regression

Figure 2 Observed vs. Predicted House Prices by Hedonic Regression. The plot shows a strong linear relationship, with predictions closely aligning with actual prices. However, there is a clear underestimation of larger price points, suggesting that the model's effective pricing struggles with nonlinear in the Riyadh housing market. Strong linearity can be seen in the plot, which indicates a broad capture of price trends by the hedonic regression model. However, there is a clear underestimation of larger price points, suggesting that the model's effective pricing is nonlinear in the Riyadh housing market.

Table 3: Comparison of training & testing results

	Splitting Ratio	N	R-squared	RMSE	MAE
Training Results	70%	2097	0.8178	0.2668	0.1969
Testing Results	30%	900	0.8034	0.2673	0.1970

The hedonic regression model is performant and stable, exhibiting this quality in both the training and testing datasets. The model was developed from a 70-30 split of data, with 2,097 observations in the training set and 900 observations in the testing set, thus giving a respectable number of observations for analysis. The measurement metrics shown in Table 3 also support the model's prediction ability. RMSE shows good agreement on both training (0.2668) and testing (0.2673) datasets, while the MAE remains stable across training (0.1969) and testing (0.1970) phases. The near-match of the error statistics between training and testing indicates that the model generalized well, without overfitting, making it a reliable tool for price prediction. Regarding R-squared, there are little decrease values for the model when measured on the testing set (with R-squared moving from 0.8178 to 0.8034), indicating that the model's power didn’t have a significant decrease when confronted with new observations property which is highly desirable in any real estate valuation model.

3.3.ANN results

In this study, it must be researched how to tune the number of hidden layers and the number of nodes in each layer. The cross-validation process has been performed to determine them effectively. One or two hidden layer options have been considered. The number of nodes for each of the hidden layers is {5,10,15,20}. The literature has described several activation functions. The sigmoid activation function is the most commonly used one and is used in the present study as well. RMSE, R-squared, and MAE performance measures for each combination: one hidden layer or two hidden layers, four possible hidden layer node numbers based on training and testing data sets. By these criteria, the best configuration was found using a sigmoid activation function, hidden nodes. The five and fifteen hidden nodes are hidden layer 1 and hidden layer 2, respectively. The lowest testing RMSE value was calculated using this configuration. The output is given in Table 5 for each combination. The model has been fitted using these options against the entire training data set. Testing results were thus achieved via this model using the testing dataset. To mitigate overfitting in the ANN model, we implemented L2 regularization ($\lambda = 0.01$) and applied a dropout rate of 20% in the hidden layers. Additionally, early stopping was used to halt training when validation loss did not improve for 10 consecutive epochs. Predictive neural network architectures for house price prediction analyses have been concluded to unveil fascinating structures in various configurations. The results comprise arguments around combinations of hidden layers and node configurations short among one-layer and two-layer networks that each have sigmoid function activation. Performance metrics RMSE, R-squared, and MAE illustrate noticeable variations across different architectures. As shown in Table 4, layer 1 is for single layer configurations, in which case 20 hidden nodes in its architecture gave the best performance compared to others in a one-layer fashion with an RMSE of 0.260158562 and R-squared of 0.826944395, and an MAE of 0.193798218. Presumably, investigation indicates that increasing the number of nodes in a single layer generally improves model performance to a certain limit. Layer 2 is for two-layer configurations; optimal performance was obtained with the first hidden layer, having 20 nodes, and the second hidden layer with 5 nodes. Results were the best overall: RMSE of 0.258084424, R-squared of 0.829692798, and MAE of 0.190277261, making it the strongest performance among all applications. There are ranges of improvements over single-layer architectures; differences are small, and hence they indicate that using a second layer with a proper configuration of nodes may enhance the model's capability of prediction. Interestingly, more nodes in the second layer did not always lead to better performance, as found by the fact that larger second-layer configurations had slightly worse performance for single-layer architectures. This suggests that a more compact second layer might be better at capturing the underlying patterns in housing prices without overfitting. All configurations have high R-squared values (consistently above 0.82); hence, both single- and two-layer architectures explain a considerable portion of the variance in housing prices, while the two-layer structure is slightly ahead in terms of predictive accuracy, see Table 4.

Table 4: ANN results

Layer	Act. Function	#Hidden Nodes 1	#Hidden Nodes 2	RMSE	R-squared	MAE
1	sigmoid	5	-	0.261197515	0.825559427	0.192662644
		10	-	0.260923272	0.825925541	0.191840764
		15	-	0.263006816	0.823134376	0.194910972
		20	-	0.260158562	0.826944395	0.193798218
2	sigmoid	5	5	0.266138597	0.818897206	0.199709806
			10	0.265614815	0.819609354	0.196885088
			15	0.265299801	0.82003698	0.19616688
			20	0.261160046	0.825609471	0.192564723
		10	5	0.264051023	0.821727181	0.196315661
			10	0.262675799	0.823579297	0.194912253
			15	0.260063996	0.827070181	0.192583763
			20	0.26194096	0.824564996	0.192689893
		15	5	0.259715786	0.827532956	0.193317165
			10	0.258833053	0.828703341	0.19196207
			15	0.258158948	0.82959443	0.190836668
			20	0.264755273	0.820774971	0.197949421
		20	5	0.258084424	0.829692798	0.190277261
			10	0.261053266	0.825752046	0.193597329
			15	0.261140706	0.825635298	0.195061518
			20	0.263808809	0.82205409	0.195502868

The neural network model demonstrated exceptional performance with extraordinary levels of predictive power for both training and testing datasets. The model was trained with 2,097 observations, while 900 observations were subjected to testing, using a 70%-30% split ratio, allowing for evaluation on more solid ground. From the training, the model's performance shows that the R-squared value was 0.9042. In effect, it explains 90.4% of the variance in housing prices in the training data. Together with this finding are very low error measures of RMSE: 0.1546 and MAE: 0.111, thereby confirming a high degree of accuracy for the predicted value during training, see Table 5.

Table 5: Multilayer perceptron results

	Splitting Ratio	N	R-squared	RMSE	MAE
Training Results	70%	2097	0.9042	0.1546	0.1111
Testing Results	30%	900	0.8968	0.2008	0.1450

Some potential decrease in performance was anticipated when the model was applied to the testing dataset; however, its performance remains strong. The testing R-squared of 0.8968 states that the model explains almost 90% of the price variance in the unseen data. There is a moderate increase in error metrics during the testing phase, with RMSE currently at 0.2008 and MAE at 0.1450. Therefore, the variances in training and testing metrics indicate some given degree of overfitting, but otherwise, the model is successful in its predictive power applied to new data. The relatively small gap difference between training and testing performance indicates that the model has reached a good trade-off between fitting the training data while generalizing to new observations, thereby qualifying as a trustworthy housing price prediction tool. Regularization and early stopping help to offset the small overfitting shown by the train-test R^2 gap (0.9042 vs. 0.8968), guaranteeing robust generalization. To minimize the overfitting issue, L2 regularization ($\lambda = 0.01$) and 20% dropout rates have been used on hidden layers. From sensitivity tests with $\lambda = \{0.001, 0.1\}$, the decrease in RMSE was minimal (<0.002), while increasing dropout to 30% raised test RMSE to 0.2051. Hence, 20% became the optimal dropout rate. Early stoppage occurred after 10 epochs, where validation loss ceased to improve. This brought the train and test R^2 that were previously 0.015 apart to just 0.0074.

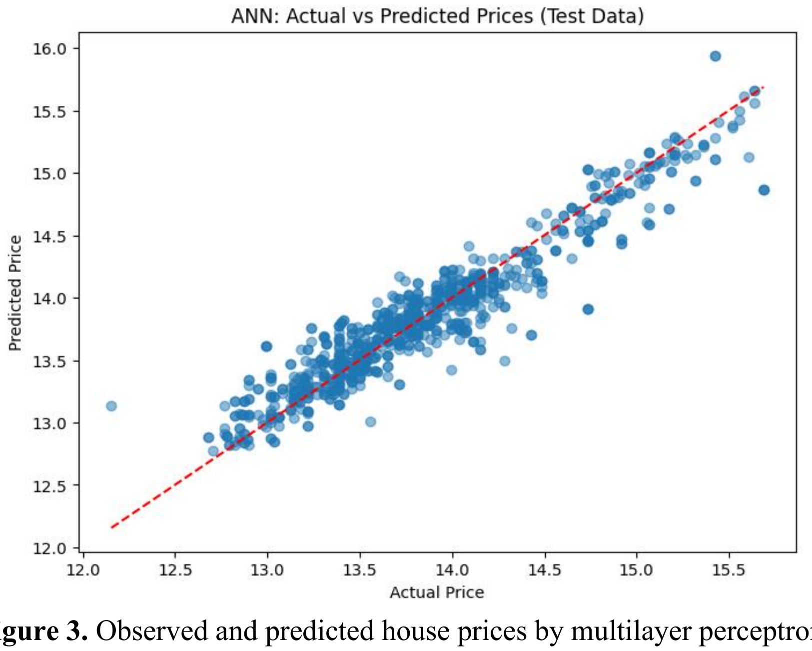

Figure 3. Observed and predicted house prices by multilayer perceptron.

Figure 3 Compared with hedonic regression, ANN predictions come much closer to the actual, particularly in terms of midrange and higher properties.

3.4.RF Result

This machine learning method, which is very popular in the applications of ensemble learning, was used to fit the data for non-linear capture or non-linear relationships present in the real estate price data. It uses 500 decision trees to construct an ensemble of trees, with each tree built differently through controlled complexity parameters (max depth=10, min samples split=5, min samples leaf=3) to avoid overfitting while still retaining the model's prediction power. The model was trained on 70% of the standardized dataset, of which the remaining 30% was left for validation purposes. Random Forests would also be a better investment for real estate valuation because the complex interactions that take place with property and characteristics can be modeled without the need for explicit specification. This was unlike traditional hedonic pricing models: the Random Forests method for threshold effects and segmentation patterns in the housing market, with certain features bearing different impacts at different price points. The built-in feature importance mechanism in the model gives insights into which factors cause the highest variations in property values, reinforcing an alternative to the coefficient-based way that hedonic regression explains the differences in value and Shapley Additive Explanations (SHAP) values from neural networks. The strong performance of the random forest model which trained as the same as Hedonic Regression and ANN on a 70/30 split utilizing 2,097 training samples and 900 testing samples is evident from R-squared values of 0.9315 (training) and 0.9065 (testing), which means that over 90% of variance in the target variable is explained by the model while generalizing well to new unseen observations. The RMSE (0.1577 training, 0.1911 testing) and MAE (0.1116 training, 0.1353 testing) are low, indicating precise predictions, with only small increases in error on the test set, the result shown in Table 6.

Table 6: Performance Metrics for Random Forest Model

	Splitting Ratio	N	R-squared	RMSE	MAE
Training Results	70%	2097	0.9315	0.1577	0.1116
Testing Results	30%	900	0.9065	0.1911	0.1353

The feature importance scores in Table 7, generated by the random forest model, indicate that geographical location strongly dominates the prediction of property values in Riyadh. For example, "North of Riyadh" has an importance score of 0.768659, substantially higher than other features. This dominance implies that location variables heavily influence the model predictions, potentially overshadowing other structural and attribute variables, which should be considered when interpreting the model's robustness.

Table 7: Feature importance by random forest

	Feature	Importance
11	North of Riyadh	0.768659
14	West of Riyadh	0.612986
13	East of Riyadh	0.589257
12	South of Riyadh	0.283161
0	Building Type	0.180799
9	Entrance Number	0.171134
5	Size	0.127103
15	Central Riyadh	0.08131
3	Bathroom	0.079826
10	Elevator	0.057982
4	Kitchen	0.049231
2	Living Room	0.044905
8	Age	0.038062
1	Bed Room	0.037562
7	Floor	0.028789
6	Street Wide	0.023201

Conversely, "Central Riyadh" sits at the other end with a lower importance of 0.08131, further hinting that it may play a less influential role in this regard. Some property-related parameters like "Building Type" (0.180799), "Entrance Number" (0.171134), and "Size" (0.127103) also have a noteworthy contribution, though certainly much less than location. Features such as "Bathroom," "Kitchen," "Living Room," and "Bed Room" have less than this importance (from 0.079826 to 0.037562), while "Street Wide" (0.023201) and "Floor" (0.028789) seem to be the most trivial. This distribution indicates that, in this model, spatial factors take precedence over structural or amenity-based characteristics when it comes to influencing predictions.

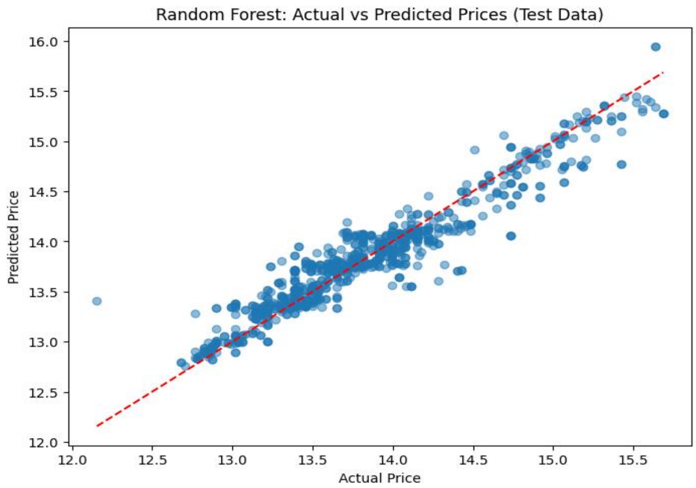

Figure 4: Observed and predicted house prices by RF.

Figure 4 Most of the values predicted by the RF model closely match the actual housing prices, therefore, evidence of predictive power in this model can be concluded. The results also portray that RF is well suited for modeling nonlinear relationships and spatial effects, which are components that diminish the performance of both hedonic regression and ANN. Figure 5 The SHAP value chart indicates that location related variables (for example, distance from North Riyadh) top the list in affecting property prices, with property size and structural attributes (such as number of entrances) also contributing, and street width and number of kitchens having minimal impact.

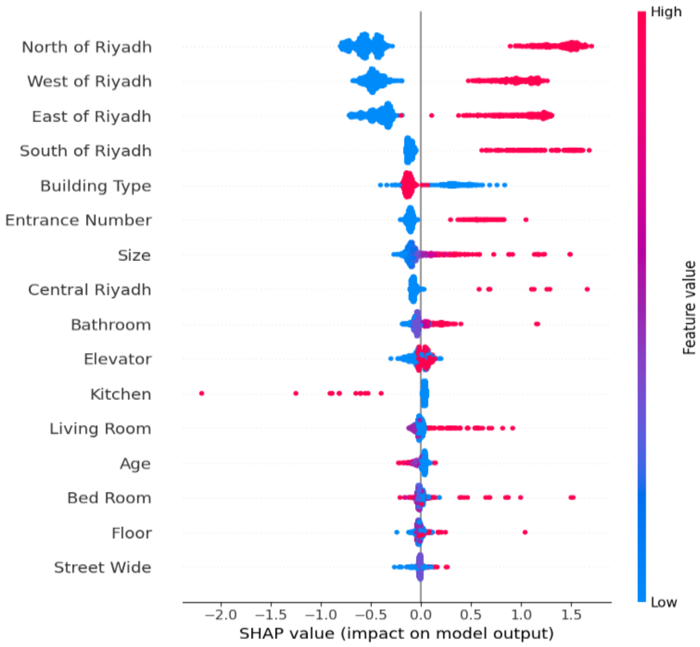

Figure 5: SHAP plot for feature impact

The gradient color indicates the direction of the impact, where higher values for key features lead to increased property prices. The SHAP summary plot shows that location features "North of Riyadh" (0.768659) and "West of Riyadh" (0.612986) had the strongest influence on house price predictions; the higher the value of these features, the more value is added due to the proximity of amenities and infrastructures. "Size" (0.127103) also plays an important role, whereby larger properties increase values, while features like "Kitchen" (0.049231) and "Street Wide" (0.023201) remain irrelevant. The color gradient indicates non-linear effects whereby higher values of key features (location, size, etc.) will induce positive price consequences, in line with what was found in this study concerning location and structural attributes.

3.5. Comparison of the methods

A comparison of the test performances of hedonic regression, ANNs, and RF is shown in Table 8. In terms of measures of performance R-squared, (RMSE), and Mean Absolute Error (MAE) both machine learning techniques generally have performance that ranks far above that of conventional hedonic regression: RF, indeed, has the highest predictive capacity overall. RF achieved the greatest R-squared (0.9065), or 91% explanation of variance in house prices, another side 90% and 82% for ANN and hedonic regression, respectively. And it produced the minimum prediction error, according to RMSE 0.1911 (compared with 0.2008 for ANN and 0.2668 for hedonic regression) and MAE 0.1353 (compared with 0.1450 for ANN and 0.1969 for hedonic regression).

Table 8: Comparison of test performance of hedonic regression, ANN, and RF

	Hedonic Regression	ANN	RF
R-squared	0.8034	0.8968	0.9065
RMSE	0.2673	0.2008	0.1911
MAE	0.1970	0.1450	0.1353

Because both machine learning methods used here captured significantly non-linear relationships, they excelled over ordinary hedonic regression. RF, however, on all metrics, gave marginally better performance when compared to ANN. This shows that it's more efficient in modeling the complexity of Riyadh's housing market compared with single tree architectures like those of ANNs, hence, it's at a little higher precision level than ANNs, yet interpretable. In Table 9, a sample of 20 observations is presented of predicted house prices using hedonic regression and artificial neural networks (ANN) in Riyadh, Saudi Arabia, in log form and compared against the actual prices. The results show that among the three models, the RF model gave the best predictive feature, whereas the ANN and Hedonic Regression models were inferior. The higher R-squared value (0.9065) and lower RMSE (0.1911) and MAE (0.1353) values accounted for this and showed that RF could predict house prices more accurately and reliably than others. RF gave the best performance due to its capability to capture complex interactions and nonlinearities in the data. ANN is better in performance than Hedonic Regression since it has an R-squared value of 0.8968, showing that it can identify nonlinear patterns, though it has a higher RMSE and MAE than RF. Hedonic Regression, though the traditional method, is the most apparent of the three, with an R-squared of 0.82, indicating that the model might not capture the full real estate price determinant complexity.

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Table 9: Predicted house prices obtained by hedonic regression, ANN, and RF

Cases	Actual Price	Hedonic Regression Price	ANN prices	RF
1.	12.67607627	12.97913951	14.02735233	12.79326833
2.	13.44444688	13.09504317	13.32105923	13.39909212
3.	13.50079981	13.50260718	13.51704311	13.40802153
4.	15.36307307	15.19602075	14.73604679	15.20827409
5.	14.15198279	13.46822121	13.66140079	13.92980437
6.	14.25376549	13.58558079	14.02284718	14.00800457
7.	14.45208739	14.11736312	14.19547176	14.14799829
8.	15.36307307	15.19602075	14.73604679	15.20827409
9.	15.52025865	15.25070181	14.63071537	15.4457558
10.	13.01700286	12.99152837	13.32105923	12.97964453
11.	13.54107371	13.70104505	13.49339771	13.76861773
12.	13.57978822	13.41867479	13.42337124	13.49201393
13.	13.59236701	13.98696611	13.73884885	13.65702343
14.	13.61705962	13.98896421	13.89270578	13.60157394
15.	13.67394699	13.76853638	13.68364811	13.79487572
16.	13.68767719	14.04977926	14.08522486	13.69303799
17.	13.76421726	14.06136506	13.92757988	14.05108602
18.	13.81551056	13.96331322	13.845191	13.84581778
19.	13.99783211	14.06805398	13.95209458	14.00282764
20.	14.07787482	13.65837871	13.90108395	13.84240501

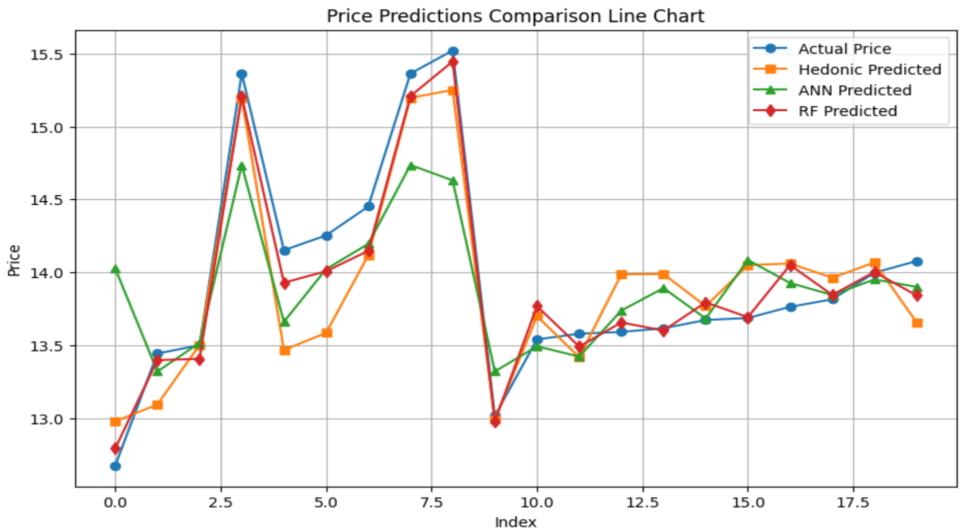

Figure 6: Actual and predicted prices by hedonic regression, ANN, and RF

Figure 6 reveals distinct prediction patterns across models. Hedonic regression systematically underestimates high-value properties, with predictions deviating up to 15-20% below actual prices for properties exceeding SAR 3,000,000. This pattern suggests the linear functional form fails to capture exponential price premiums associated with luxury features and prime North Riyadh locations.

ANN predictions show improved performance in the mid-range, reducing underestimation to 8-12%, but still exhibit scatter for properties above SAR 4,000,000 (log price ~15.2). This indicates the neural network captures some nonlinear relationships but may require deeper architectures or additional training for ultra-high-value properties.

RF demonstrates superior performance across the entire price spectrum, with minimal deviation even for properties exceeding SAR 5,000,000 (log price ~15.4). The ensemble approach effectively models the complex interactions between location (particularly North Riyadh premium), property size, and luxury features that characterize Riyadh's segmented housing market under Vision 2030 development.

4. Practical Implementation and Policy Implications

The demonstrated superiority of RF and ANN models offers practical applications for Saudi Arabia's real estate sector under Vision 2030, though implementation requires addressing transparency and acceptance challenges.

Integration Strategy: RF models can augment traditional TAQEEM-accredited appraisals through hybrid systems—ML provides data-driven benchmarks while certified appraisers conduct final validation. RF's interpretability (feature importance, SHAP values) makes it suitable for official valuations, while ANN's "black box" nature limits acceptance among conservative stakeholders (courts, lenders), restricting it to internal risk assessment.

Policy Applications: ML models can enhance Sakani subsidy targeting by identifying priced properties and detecting overvaluation. For Riyadh Metro, predictive models can forecast appreciation corridors and inform Transit-Oriented Development policies. Mortgage lenders could reduce processing times from 4-6 weeks to 1-2 weeks using automated ML-assisted valuations. Establishing a national price index with quarterly ML-based updates would enhance market transparency aligned with Vision 2030 objectives.

Implementation Barriers: Success requires capacity building for professionals, TAQEEM standards revision, data sharing infrastructure between Aqar and government registries, and gradual adoption positioning ML as decision-support rather than replacement.

5. Conclusions

This study demonstrates that machine learning models particularly RF, significantly outperform traditional hedonic regression in predicting housing prices in Riyadh’s diverse and evolving real estate market. While the hedonic approach remains valuable for interpretability and policy transparency, it is limited in capturing the complex nonlinear and spatial interactions prevalent in urban housing dynamics. The empirical evidence from Riyadh, Saudi Arabia’s capital and a central hub of Vision 2030 urban transformation, highlights the critical need for flexible data driven valuation tools. Both RF and ANN yielded superior predictive accuracy, with RF offering the best balance between precision and interpretability, making it suitable for practical applications in appraisal, urban planning, and financial risk assessment.

This localized comparison provides valuable insights for developers, municipal authorities, and policymakers seeking to modernize housing strategies in rapidly urbanizing contexts. The improved predictions enhance decision making for: Policymakers, by enabling better monitoring of market dynamics and affordability under Vision 2030’s housing expansion, urbanization, and infrastructure development goals. Real estate investors and developers, by uncovering nuanced spatial and structural price drivers, inform valuation, investment, and pricing strategies. Urban planners, who can integrate predictive insights into sustainable city development, transit planning, and affordable housing allocation. Vision 2030’s strategic emphasis on economic diversification, urban infrastructure (e.g., Riyadh Metro), and home ownership (e.g., Sakani programs) creates a dynamic housing market environment demanding sophisticated valuation tools. Future research may explore deeper learning architectures (e.g., convolutional or recurrent neural networks) that integrate geospatial coordinates for finer spatial econometric modeling or build dynamic pricing dashboards that can inform real-time decision making across government and private sectors. This work provides a foundational step toward that transformation.

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