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Using Machine Learning Algorithms for Housing Price Prediction: The Case of Islamabad Housing Data

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Abstract: House price prediction is a significant financial decision for individuals working in the housing market as well as for potential buyers. From investment to buying a house for residence, a person investing in the housing market is interested in the potential gain. This paper presents machine learning algorithms to develop intelligent regressions models for House price prediction. The proposed research methodology consists of four stages, namely Data Collection, Pre Processing the data collected and transforming it to the best format, developing intelligent models using machine learning algorithms, training, testing, and validating the model on house prices of the housing market in the Capital, Islamabad. The data used for model validation and testing is the asking price from online property stores, which provide a reasonable estimate of the city housing market. The prediction model can significantly assist in the prediction of future housing prices in Pakistan. The regression results are encouraging and give promising directions for future prediction work on the collected dataset.

Keywords: machine learning for regression; housing dataset; Property stores; house price prediction; housing property value; real estate market;

1. Introduction

The real estate market in Pakistan is a widespread trade, and with Projects like CPEC, the property dynamics are changing quickly. Investors, as well as individuals, want to invest money in the housing sector. Buyers and owners observe real estate trends, particularly in the housing market; these trends also reflect the economic situation and social sentiment of any developing country. House price estimation is a significant financial decision for individuals working in the housing market and potential buyers. From investment to buying a house for residence, a person investing in the housing market is interested in the potential gain. To understand this study's background, We first overview the housing market of Pakistan and then give an overview of the dataset used in this study.

There are many factors which determine the houses prices. If we look into real estate in general, then an increase in the real estate market is explained by the rise of the particular area's inhabitants' income. However, careful analysis suggests that we can only temporarily suggest that the prices of real estate are increasing due to these factors, such as demand-oriented variables and others. Therefore, we can conclude that the factors can be changed from time to time.The house prices are based on income of the inhabitants of the area, house stock supply and the payment system, whether accept installment or require cash payment.

Other essential variables can include whether the price is the affordable, unemployment rate, demographics, and others, but we can explain house prices as a general income function.In this study do not consider all the possible variables that can be used to predict housing prices. In this study, we use only the housing data available from the property websites to predict the housing prices by looking at the recent trends.Pakistan's economy is slowly on the way towards recovery. The unemployment rate is on a downwards stream, and consumer spending is going up. Nevertheless, the growth rate is still struggling, which indicates that the Pakistan economy still has a long way to go before it is up and running.

In Europe and other advanced countries, real estate companies challenge developing algorithms that can forecast real estate property prices more accurately. Researchers are using some well-known housing datasets, e.g., Boston and King city USA datasets. One of the gaps for Pakistan is the absence of a comprehensive housing dataset. Some real estate property sites in Pakistan provide a reasonable estimate of the Pakistan housing market, but currently, they are not using house price forecasting tools. Websites like Zillow[1], a US real estate market place organizes competitions on kaggle[2] to encourage researchers to come up with accurate house price forecasting algorithms. Since such challenges are not part of the Pakistan housing market yet, making it very difficult for a research scholar to develop such forecasting algorithms for the Pakistan real estate housing data, the only sources of housing data are these online property stores.In the Pakistan real estate market, there are currently no Machine-based forecasting tools used to estimate houses or any other real estate properties. There are some blogs and magazines where human real estate market experts advise Pakistan real estate forecasts. Lack of scientific research competitions for forecasting Pakistan's housing prices and hence lack of housing dataset make housing Price prediction for Pakistan real estate a difficult and challenging task.

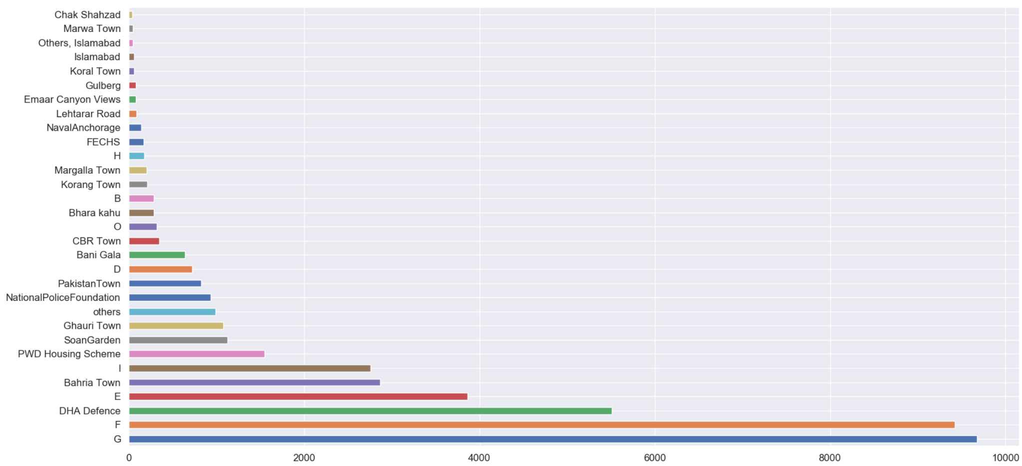


Figure 1. Properties count based on locations

Figure 1 displays the Property counts of the dataset with respect to sectors of the capital Islamabad. We collect the dataset for this study from the leading property websites in the country. The dataset for this study is from online property stores based in Pakistan. These websites contain details of property listings from various cities of Pakistan. The dataset for this study is of Islamabad. The dataset is in tabular textual format consisting of 23 columns and 44647 rows collected over a period of one year.

1 www.zillow.com
2 www.kaggle.com

2. Related Work

In literature, the approaches used for house price prediction can be classified as regression models, machine learning models, and hybrid models.A variety of research work has been done to estimate housing prices. Gaussian Processes (GP) for regression Model benefit from the London housing dataset's spatial structure; for this purpose, smaller local models are developed, which works independently from each other. Once local models are trained, the overall predictions are obtained by recombining predictions from local models. For generating visualization to clients through mobile [1], the model is trained at the server-side, and prediction is generated for the user via a mobile app.

Linear Regression and Gradient Boosting methods are used by sangani et al. [2] to predict Zillow Estimation. Zillow is offering competition on Kaggle to develop the most accurate property value forecasting algorithm. They used property data to train their linear regression and gradient boosting models with which they make predictions about other properties. For gradient boosting models, they use grid search to fine-tune their model's hyperparameters. Oladunni et al. [3] reduce errors in the Hedonic housing regression model by investigating Spatial Dependency substitutability of submarket and geospatial attributes. The model is trained using best subset linear regression and regression tree algorithms. Bayesian information criterion and residual mean deviance are used as performance matrices.

Ahmed et al. [4] design a neural network-based model for predicting housing Market Performance. This model is trained through a historical market performance dataset to predict unforeseen future performances. The model testing and validation show that the error in predicting his Neural Net is in the range between –2 and +2 percent.To predict the Singapore housing market, Lim et al. [5] design neural networks. They used two algorithms for prediction, the multilayer perceptron, and autoregressive integrated moving average. The model with high accuracy score is used for prediction, and the model with lower mean square error (MSE) of the ANN models shows that ANN is best over other predictive tools. Chica et al.[6] designed Cokriging a Multivariate Spatial Method for predicting Housing Location Price. This method estimates correlated spatial variables, interpolated maps of house prices are created, providing information about house location prices to appraisers and real estate agents. During the experiment, housing location price prediction value is estimated using methods: isotopic data cokriging and heterotopic data cokriging. Results from both methods are compared, and prediction from the best method is selected.

Bahia et al. [7] used a data mining model using an Artificial Neural network to the real estate market. Two network models were developed during the study FFB and CFBP. Both of these models were trained using the Boston dataset, and the performance matrix used was regression value. The CFBP prediction results are best, and the regressional value is .964; the study suggests that CFBP prediction accuracy is 96 percent. Stevens et al. [8] used text mining to predict housing prices. His prediction price involves pricing indicators, e.g., selling price, asking price, and price fluctuation. This study shows that the SGD classifier performed best for all pricing indicators and achieved the best results. The study uses stemmed n-grams for classification and regressions. R2 Matrix performance value for prediction is 0.303. The study suggests that both of these results are good due to the task complex nature.

Nissan et al. [9] used various algorithms to Predict real estate property prices in Montreal. The study suggests a prediction model that predicts asking and selling prices based on features, such as location, area, rooms, nearest police station, fire station, etc. They used many regression models for regression prediction. These regression methods include linear regression, SVR, kNN, regression Tree, and Random Forest Regression. The proposed prediction models predict the Asking price with an error of 0.0985 and the selling price with an error of 0.023.

Nghiep et al.[10] compared multiple regression analysis to artificial neural networks (ANN) using three different-sized training sets of single-family houses. The prediction Model uses features, e.g., area, number of bathrooms and bedrooms, the property build year, which shows how much property is old in terms of years, number of quarters, selling status, and whether or not the property has a garage or carport. The researchers proposed that while MRA performs best on smaller-sized training sets, ANN was found to outperform as the dataset size increases.Byeonghwa and Jae [11] applied various prediction techniques to predict prices of houses in Fairfax County, VA. They build various models on 5359 townhouses. They evaluated and compared these models and proposed that RIPPER, Bayesian, and AdaBoost. RIPPER is best than other prediction models. They also applied Naive Bayesian to the same dataset, but RIPPER algorithm performance is outstanding for housing price prediction.

3. Materials and Methods

We present the experimental design in three stages, where the former presents data collection, and second presents Preprocessing steps, and the third presents regression models for house prices prediction.

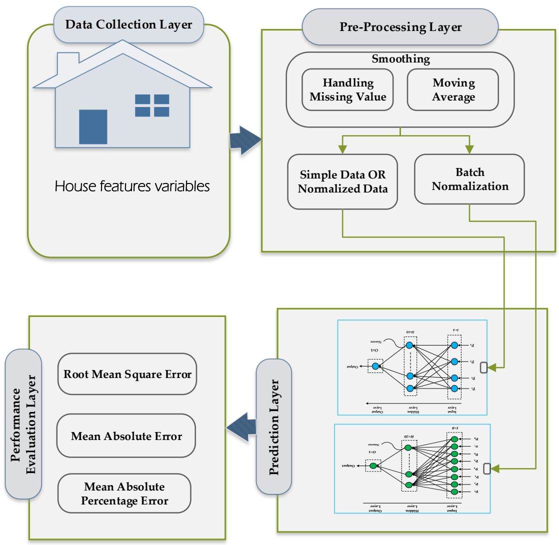


Figure 2. Experimental Design.

3.1. Data Collection

Data is collected using scraping software that collects data from the internet in a format that the machine learning model can use. When parsing, the output data is interpreted by a machine, but the human can not understand it easily. Data scrapping is also referred to as data extraction.Data scrapping is very useful as if humans perform the data collection from the internet, and there are many chances of error as machines transfer data between programs in the form of data structures that provide high integrity of the data. However, the script is written for a pre-determined format, and it may not be necessary that the data is always in the given format. The data may have issues in terms of data consistency and correctness. Therefore, data scrapping only collects raw data and requires extensive preprocessing and, in some situations, also requires human involvement.The data scrapping activity is primarily dependant on the Internet sources from where data is being collected and can not be fully automated. For example, in the case of you scraping data from the website, the best format is that if the developer has assigned to each unique HTML element, an attribute ID and an attribute of the class are assigned to each item of the same group. This helps to create a script in almost any programming language. Comparative study[12] of open-source scraping tools suggests that scrapy is the best open-source tool for scrapping, So in this study, We use Python *scrapy* library for creating our crawler.

However, note that web scraping from well-settled companies is not trivial as the companies use defensive algorithms and software to protect un-wanted access to their website. Most of them are blocking any type of script in their *robots.txt*. So the idea is to write a script that can scrap data intelligently like a human being. This is achieved by automating human behavior when browsing a website. For example, if scrapping an entry is delayed by 5 seconds or 10 seconds, the system may not recognize data extraction from the website and could consider it a regular activity.

Data scraping is done on publicly available data via browser either without login or after authentication to their website. In the case of using SQL Injection to hack their database is a saviors internet offense.

Web search engines, e.g., Google, yahoo, bing, and others, play an essential role in reaching a website. For example, we type a keyword, and after the query is entertained, the search engine gives us results based on that query. This helps find a data host, and it gives both benefits to the data host and the person who is scraping. The Mechanism search engines use the same as web scraping, but they are not blamed for data scraping as the data is used for the user's convenience.

If we consider Google, Google has two part of their search engine, one Googlebot a software bot which crawls billions of web pages from the websites on the internet and is stored in the Google data hosts and another part of the system is an algorithm which entertains the user-queries based on the data crawled and displays results to user with the help of a ranking algorithm.

In regard to whether web scraping is legal or illegal, Michael Mahoney observes [13] that legal action is taken against airline price aggregators such as Orbitz Kayak and Expedia. Another example in this regard is Facebook. Facebook has a history of suing third-party applications that have accessed and republished Facebook user data[14].

Another exciting example is Craigslist [15] which provides services like Padmapper, 3Taps of an improper gathering of their information and reposting it as a map interface which is plotted as the chart on the location of the user-generated ads. The author states there is "no direct legal protection for databases. However, data hosts can file a case against scraper if they can prove the scraper has harmed them in any way". One such example is Intel and Hamidi's case that ruled that server inconveniences do not constitute an actionable harm [16]. Scraping may consume the bandwidth of websites and, in extreme cases, crash a website or server.

In summary, the legality of scraping by [17]: multiple instances of data hosts pairing up with scraper show that data host should seek ways to embrace scrapers that seek to improve their services. Further, the scrapers should review their business model. If a data host thinks scraper is parasitic, then he can sue the scraper. Table 1 and Table 2 presents physical, geographical and other features of the collected dataset.

Name of the attribute	Description	Data type
Area	living area in Square feet	Numeric
Bedrooms	number of bed rooms	Numeric
Bathrooms	number of bath rooms	Numeric
Dining Room	dining room? (yes/no)	Binary
Drawing Room	Drawing Room? (yes/no)	Binary
Laundry Room	Laundry Room? (yes/no)	Binary
Lounge	Lounge? (yes/no)	Binary
Garden	Garden? (yes/no)	Binary
Flooring	Flooring? (yes/no)	Binary
Study Room	Study Room? (yes/no)	Binary
Swimming Pool	Swimming Pool? (yes/no)	Binary
Central Air Conditioning	Central Air Conditioning system? (yes/no)	Binary
Build	house build type? (old/new)	Binary

Table 1. List of physical features selected for the dataset.

Name of the attribute	Description	Data type
Location	sector name of the location	Nominal
Nearby Hospitals	Nearby Hospital? (yes/no)	Binary
Nearby Schools	Nearby School? (yes/no)	Binary
Nearby Shopping Malls	Nearby Shopping Malls? (yes/no)	Binary
Maintenance Staff	Maintenance Staff? (yes/no)	Binary
Security Staff	Security Staff? (yes/no)	Binary
Nearby Airport(yes/no)	Nearby Airport(yes/no)? (yes/no)	Binary
View	house View? (good/best/normal)	Nominal
Parking Spaces	Parking Spaces? (yes/no)	Binary
Price	price of the house in PKR?	Numeric

Table 2. List of geographic and environmental features.

3.2. Preprocessing

Data preprocessing is done in order to transform the dataset into a clean dataset for better machine learning models. Data preprocessing techniques are applied to data in raw format, which is not feasible for analysis. As in our case, the data is collected from different property websites where property agents entered it, so there are missing values, data in various formats, and incorrect data. We performed data integration to combine the data from various sectors of the capital into an integrated dataset. Data transformation methods were applied to transform the data records to a format that is good for machine learning analysis.

To perform iterative analysis on data, we cleaned the dataset from missing and incorrect values. Data Wrangling, Data Munging are similar terms used in the Data Science community; data wrangling/data munging are techniques used to convert raw data into a format that is best for using the data. In our case, we converted the textual data such as yes and no to binary variables. Locations, views, and other variables were encoded into numbers for better analysis results.

We computed the binary variable Build from the year of construction of the house. The house's asking price was in various currencies and units, e.g., lacks, thousands, crore. We converted it into lacks units and PKR currency. Machine learning algorithms such as neural networks perform best on data values ranges from 0 to 1, so we scaled down our dataset values between 0 and 1 using the Min-Max scaling algorithm. Later on, for performance evaluation, the values are scaled up to their original range. Equation 1 shows how to scale down values between 0 and 1.

$$x' = \frac{x - min(x)}{max(x) - min(x)} \tag{1}$$

Figure 3 shows the Correlation between housing features, it is used to calculate the strength of the relationship of housing features i.e., Bedrooms and Bathrooms, Build, Dining Room with price feature. The Correlation Coefficient value for Bedrooms and Bathrooms with respect to price features is high than the rest of the features, which shows that price features having a strong relationship with Bedrooms and Bathrooms features, and hence these will contribute more than other features in house price prediction.

Its clear from Figure 3 that all the features except Area, Central air conditioning, location, view having some sort of relationship with the price feature. In this study, we used the Pearson correlation coefficient to measure the strength of the features variables' relationship. Pearson correlation coefficient can be calculated using Equation 2.

$$\rho = \frac{\mathrm{cov}(X, Y)}{\sigma_x \sigma_y} \tag{2}$$

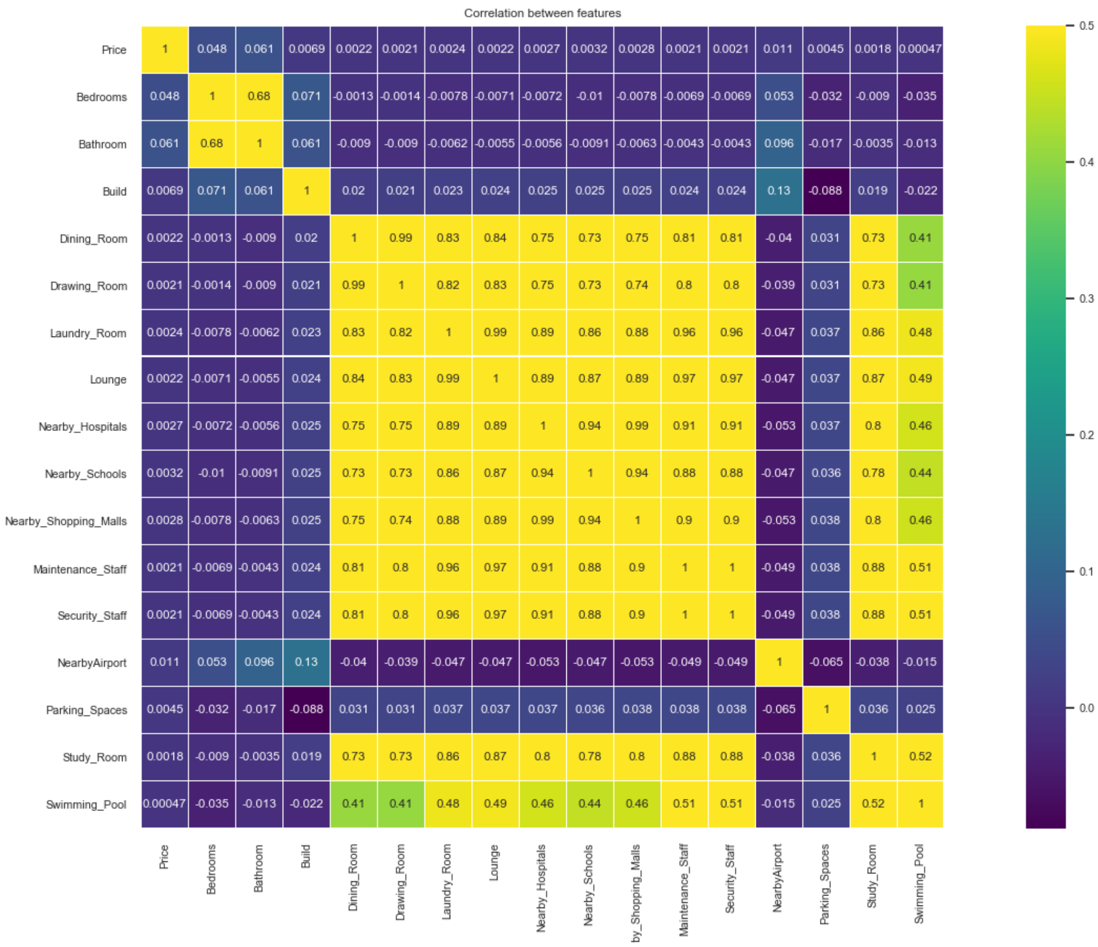


Figure 3. Correlation between features

After applying Preprocessing the dataset, we Partition the dataset into training, validation, and testing subsets. Each of these partitioned datasets is further divided into dependent and independent variables, set X and Y.

3.3. Analysis procedure

This study developed various regression models, including Intelligent machine learning-based models, and applied them to our dataset. The development toolkit used for developing our regression models is anaconda spyder. We now discuss ten machine learning regression procedures applied to our dataset.

3.3.1. Machine Learning Regression Methods

Linear regression (LR) [18] are used too much because its easy, straightforward to understand. It is one of the most basic and popular algorithms in machine learning. In this study, we build a multivariate LR Model to predict housing prices. LR Model will find the best possible line that fits the training set and then predicts the unseen house price from the test set.

We applied Support Vector Regression(SVR) [19] into the same housing dataset for housing price prediction. SVR is slightly different from the famous machine learning algorithm Support Vector Machine(SVM). The main difference is that SVM is used for classification, and SVR is used for a regression problem. In SVM, a hyperplane is used as a separation line between classes. In SVR, we define the hyperplane line for predicting the continuous value or housing price value. Other concepts, i.e., boundary line and support vectors, are the same between SVM And SVR.

We estimated the housing price prediction problem using a machine learning probabilistic model called Bayesian Ridge Regression (BRR) [20]. We estimate the house prices t be Gaussian distributed around the independent housing features. The main advantage of using BRR for house price prediction or other regression problems is that it can adapt to the data at hand, and second that it can be used to include regularization parameters in the housing price estimation procedure.

LassoLars regression [21] is one of the simple techniques to reduce model complexity and prevent over-fitting, resulting from simple linear regression. Lasso regression helps in reducing over-fitting and in feature selection. Just like Ridge regression, the regularization parameters can be controlled for better estimation of the housing prices. Elastic Net [22] first emerged as a result of critique on lasso regression, whose variable selection can be too dependent on data and thus unstable. The solution is to combine the penalties of ridge regression and lasso to get the best of both worlds. The elastic Net main aim is minimizing the loss function.

Gradient boosting regression(GBR) [23] is a machine learning that can be used to build a prediction model for regression problems like house price prediction in the form of an ensemble of weak prediction models. GBR repetitively leverages residuals patterns and strengthens a housing price prediction model with weak predictions, and makes it better. The main aim is minimizing our loss function, such that test loss reaches its minima. Random Forest(RF) [24] is an ensemble technique capable of performing both regression and classification tasks with the use of multiple decision trees and a technique called Bootstrap Aggregation, commonly known as bagging.

Stochastic gradient descent (SGD) [25] is based on some addition to gradient descent. It is an iterative method for optimizing an objective function and is mostly used as black-box optimizers. SGD can be called a stochastic approximation of gradient descent optimization. Passive Aggressive Algorithms [26] are a family of online learning algorithms. We use the Passive-Aggressive regression(PAR) model for the house price prediction problem. The idea is elementary, and the house price estimation using this regression model is better than many other alternative methods. Theil-Sen estimator is a method used for simple linear regression, and it chooses the median of the slopes of all lines through pairs of points.

4. Results

This section of the study explains the experimental results of the machine learning models used in the study for house price prediction.

4.1. Performance matrices

The performance evaluation matrices used for the evaluation of the regression models are MAPE(Mean absolute percentage error), RMSE(Root Mean Squared Error), and MAE(Mean absolute error).

4.1.1. Mean absolute percentage error

This performance measure computes an average deviation found in predicted house price value from actual listing house price values. MAPE is calculated by dividing the sum of absolute differences between the actual house price values and predicted house values by the machine learning algorithm we applied in this study with the total number of price value data items, i.e., n. Figure 4 represents the performance of machine learning methods applied in this study using performance matrix MAPE.

$$MAPE = \frac{100\%}{n} \sum_{t=1}^{n} \left| \frac{e_t}{y_t} \right| \tag{3}$$

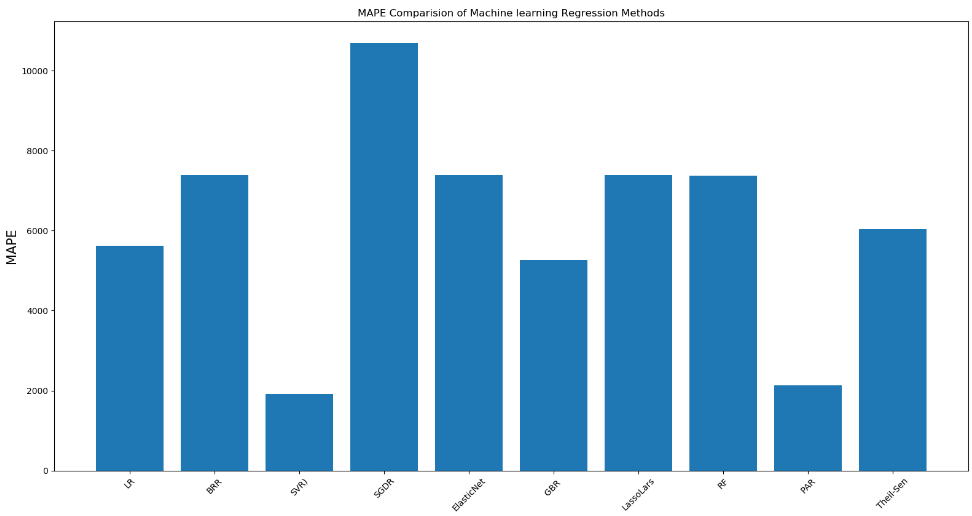


Figure 4. Performance Comparison of Machine Learning algorithms using MAPE

4.1.2. Root Mean Squared Error

MSE sometimes increases the actual error, making it difficult to realize and understand the actual error amount. This problem is resolved by the RMSE measure, which is obtained by simply taking the square root of MSE. Figure 5 represents the performance of machine learning methods applied in this study using performance matrix RMSE.

$$RMSE = \sqrt{\frac{1}{n} \Sigma_{i=1}^{n} \left(\frac{d_i - f_i}{\sigma_i} \right)^2} \tag{4}$$

4.1.3. Mean absolute error

mean absolute error is a measure of difference between two continuous variables.In our case these continuous variables are listing price value and predicted price value f the house property. Figure 6

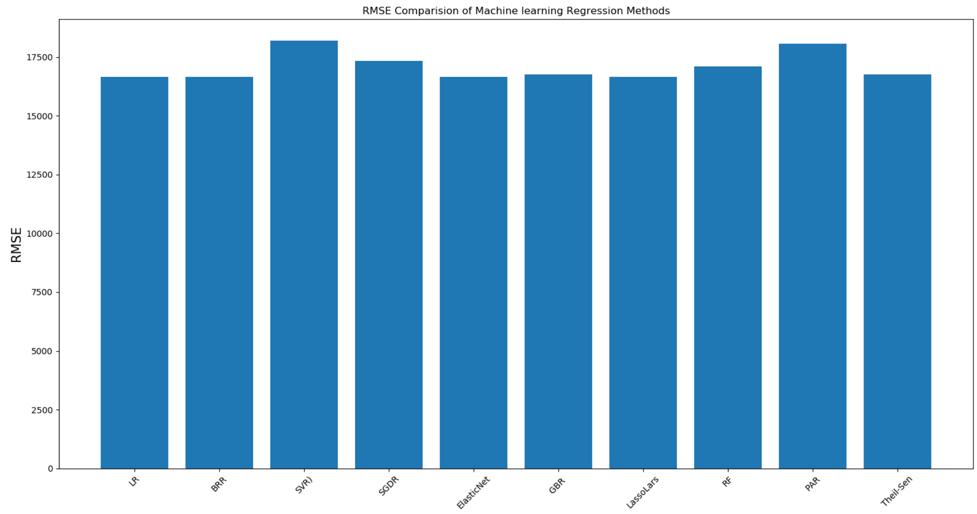


Figure 5. Performance Comparison of Machine Learning algorithms using RMSE

represents performance of machine learning methods applied in this study using performance matrix MAE.

$$MAE = \frac{1}{n}\sum_{t=1}^{n}|e_t| \tag{5}$$

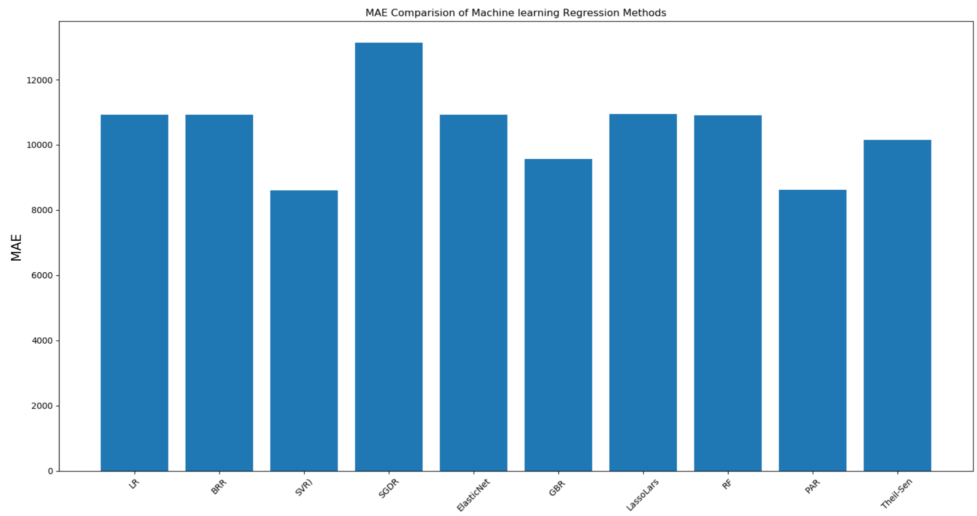
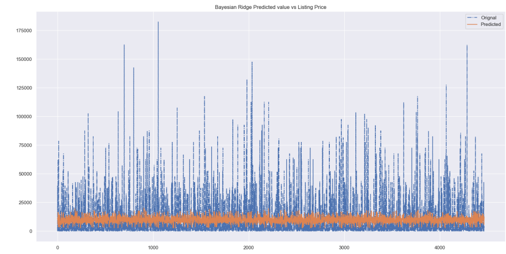
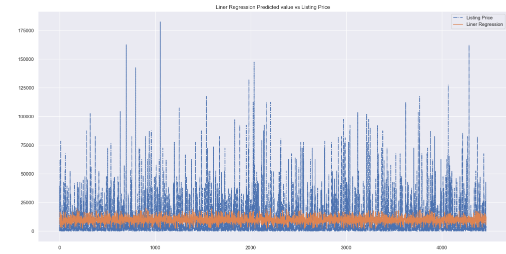


Figure 6. Performance Comparison of Machine Learning algorithms using MAE

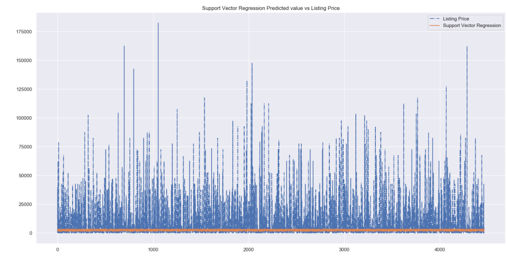
Figure 7 visualize the comparison of the house's original listing price and predicted price values by various Machine learning Algorithms. Each subfigure listing price is represented using a dashed blue color line, whereas the machine learning algorithm's predicted price value is represented using a solid orange color line. Horizontal access of the chart represents the housing property instance, and the Vertical axis represents price values.



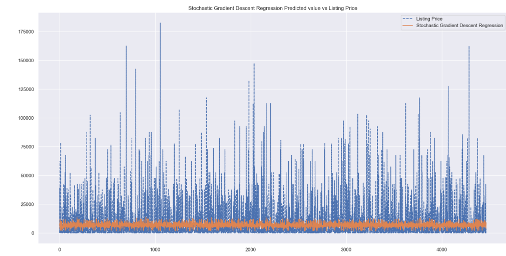
(a) Bayesian Regression



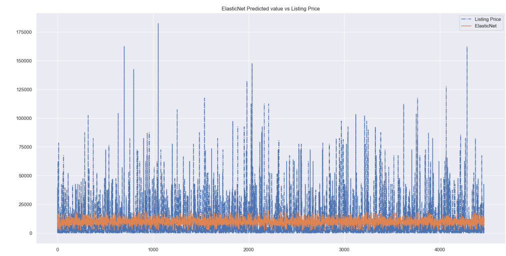
(b) Linear Regression



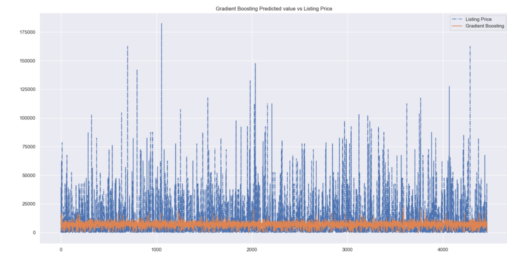
(c) Support Vector Regression



(d) Stochastic gradient descent

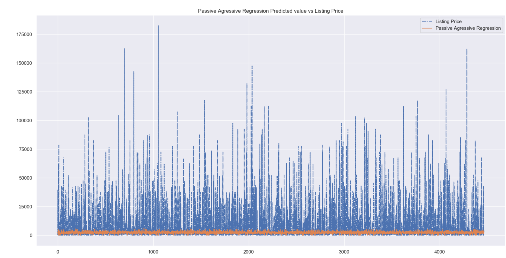


(e) ElasticNet Regression

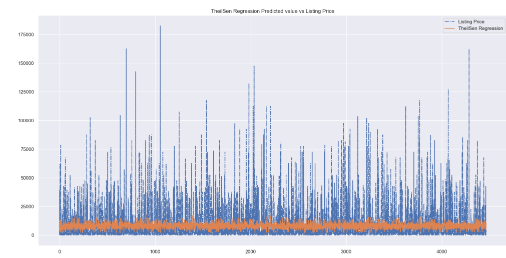


(f) Gradient Boosting Regression

Figure 7. *Cont.*



(c) Passive Aggressive Regression



(d) Theil-Sen Regression

Figure 7. Feature importance with ML models.

5. Conclusions

In this study, We have explored eleven machine learning algorithms used to develop housing price prediction models for estimating the future house pricing of the capital Islamabad. One of our

Method	MAPE	MAE	RMSE
LR	5627.9369	10928.2603	16658.4158
BRR	7383.9969	10930.6388	16661.3350
SVR	1918.4957	8595.6057	18209.5558
SGDR	10698.1442	13139.1928	17345.1444
ElasticNet	7388.1547	10927.7181	16658.2267
GBR	5267.4830	9563.4324	16772.3870
LassoLars	7382.6600	10938.5807	16670.3489
RF	7371.0746	10902.9762	17105.2596
PAR	2133.8370	8621.9391	18069.2298
Theil-Sen	6031.6336	10151.4884	16754.2930

Table 3. Comparison of regression methods performance

contributions in this study is collecting housing data and developing the first scientific housing dataset for the Pakistan housing market. Machine learning algorithms such as Passive-aggressive Regression, Support Vector Regression, and Deep learning Network can estimate the prices very close to the listing price. The results show that SVR performs best than the rest of the machine learning algorithms. In this study, we compare various machine learning regression models' performance for finding best model for a better housing price prediction. There is currently no Machine learning or other house forecast tools used in the best of our knowledge. We strongly believe that machine learning house price prediction models will help those who work in the real estate market and potential buyers in making a good house purchasing decision. In the future, this work can be used as base for several types of studies, including the real estate market, stock price prediction, oil and petroleum prices forecast. In the future, this textual tabular dataset can be used with the houses' visual features, such as images of the houses' interior and exteriors, to build a more robust, novel house price prediction. Lastly, the housing market can be influenced by other macro-economic variables such as price of gold, stock price index, property tax, and the appraised value of a property; considering these can help develop house price prediction models that can accurately estimate the house prices.

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