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Automated Real Estate Price Forecasting

Pradeep M[1], Seema Nagaraj[2]

Student, Department of MCA, Bangalore Institute of Technology, Karnataka, India[1]

Assistant Professor, Department of MCA, Bangalore Institute of Technology, Karnataka, India[2]

Abstract: This study presents the application of machine learning techniques to the prediction of real estate/house prices on two real datasets that were obtained from Kaggle, one from Melbourne developed by Anthony Pino and the other from Boston created by D. Harrison and D.L. Rubinfeld. There is a dearth of literature regarding machine learning research on housing price prediction in India. This work attempts to develop this prediction engine for user use in the real world by reviewing the use of current machine learning methods on two radically dissimilar datasets. The results show that altering the algorithms can have a significant impact on accuracy. Furthermore, a subpar dataset may have a detrimental impact on the predictions. It also offers enough evidence to determine which algorithm is most appropriate for this task.

Keywords: Machine Learning, Real Estate, House Price, Price Prediction, Algorithm.

I. INTRODUCTION

Nowadays, machine learning (ML) is an essential component of research and industry. Through the use of algorithms and neural network models, computer system performance is gradually increased. Using sample data, often known as "training data," machine learning algorithms automatically create a mathematical model that helps them make judgements without having to be explicitly trained to do so.

Real estate organisations purchase properties to operate a business, while individuals purchase homes to live in or invest in. In any case, we think that everyone ought to receive exactly what they pay for. In the housing market, overvaluation and undervaluation have long been problems, and appropriate detection techniques are lacking. Broad metrics that provide a primary pass include house/real estate price-to-rent ratios. However, a thorough investigation and judgement are required to make a decision on this matter. This is where machine learning enters the picture. Using hundreds of thousands of data points to train an ML model, a solution that can reliably forecast pricing and meet the demands of all parties can be created.

This paper's main goal is to employ these machine learning techniques to curate data into machine learning models that will subsequently benefit consumers. A buyer's first goal is to find their ideal home, complete with all the facilities they require. Additionally, people search for these homes and real estate with a specific budget in mind, and there is no assurance that they will find the item at a fair price. Comparably, a seller seeks for a figure they can put on the estate as a price tag. This figure cannot be determined arbitrarily; extensive research is required to arrive at a house's assessment. There's also a chance that the product will be underpriced.

II. LIMITATIONS OF PREVAILING METHODOLOGIES

There is a notable amount of research done in the house price prediction department but very research has come up to any real-life solutions. There is very little evidence of a working house price predictor set up by a company. For now, very few digital solutions exist for such a huge market and most of the methods used by people and companies are as follows:

Buyers/Customers:

1. When people first think of buying a house/Real estate they tend to go online and try to study trends and other related stuff. People do this so they can look for a house which contains everything they need. While doing these people make a note of the price which goes with these houses. However, the average person doesn't have detailed knowledge and accurate information about what the actual price should be. This can lead to misinformation as they believe the prices mentioned on the internet to be authentic.

2. The second thing that comes to mind while searching for a property is to contact various Estate agents. The problem with this is these agents need to be paid a fraction of the amount just for searching a house and setting a price

tag for you. In most cases, this price tag is blindly believed by people because they have no other options. There might be cases that the agents and sellers may have a secret dealing and the customer might be sold an overpriced house without his/her knowledge.

Seller/Agencies:

1. When an individual thinks of selling his/her property they compare their property with hundreds and thousands of other properties which are posted all around the world. Determining the price by comparing it with multiple estates is highly time-consuming and has a potential risk of incorrect pricing.

2. Large Real estate companies have various products they need to sell and they have to assign people to handle each of these products. This again bases the prediction of a price tag on a human hence there is room for human error. Additionally, these assigned individuals need to be paid. However, having a computer do this work for you by crunching the heavy numbers can save a lot of time money and provide accuracy which a human cannot achieve.

III. LITERATURE REVIEW

In the twenty-first century, real estate has evolved into something much more than just a basic need. not just for those considering purchasing real estate, but also for the businesses that market these properties. Real estate property, according to [4], not only satisfies a man's essential needs but also, in modern times, stands for wealth and status. Because real estate values do not drop as quickly, investing in it often appears to be successful. The price of real estate can have an impact on a wide range of people, including bankers, legislators, and individual investors. It appears that investing in the real estate industry is a desirable option. Predicting the value of real estate is therefore a crucial economic indicator. According to [3], every single company in the real estate industry nowadays is working successfully to gain a competitive advantage over rivals. The optimal outcomes must be achieved while keeping the process as simple as possible for the average person. [6] suggested creating an algorithm that can forecast home prices based on certain input features by utilising machine learning and artificial intelligence approaches. By using a few input variables to predict the correct and justified price—that is, by avoiding accepting customer price inputs and preventing errors from entering the system—classified websites can use this algorithm to directly predict the prices of new properties that will be listed.
[12] made use of the Jupiter/Colab IDE. Jupiter IDE is an open-source web application that facilitates the creation and sharing of documents using LiveCode, equations, visualisations, and narrative text. It includes tools for data translation, data cleaning, numerical value simulation, statistical modelling, data visualisation, and machine learning. [10] created a system to assist anyone in determining the approximate cost of real estate. The user can input their criteria to receive the prices of the residences they are interested in. In order to obtain references for houses, users can also obtain a sample blueprint of the house. The housing value of a Boston suburb is examined and projected in [5] utilising the appropriate characteristics and the SVM, LSSVM, and PLS algorithms.

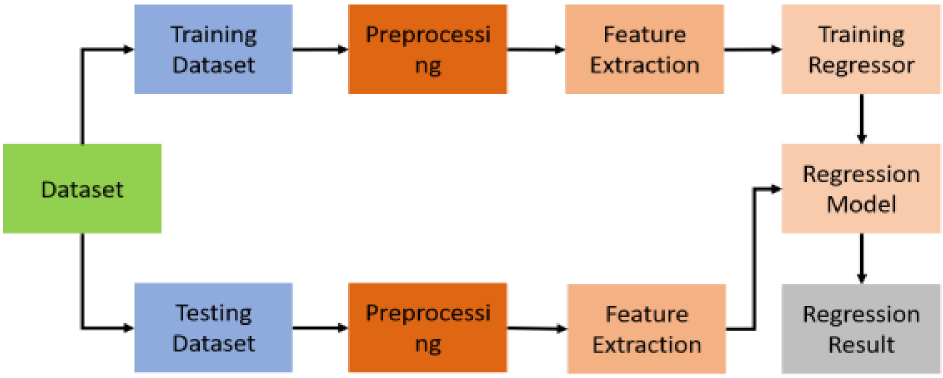
With a very minor reduction in Lasso, the Ridge and Linear Regression produce a comparable result. Regardless of strong or weak groups, there is no significant difference found across all feature selection groups. It's encouraging that the purchase prices alone, without taking into account additional factors that could encourage model over-fitting, can be used to predict the selling prices. There is also a noticeable decrease in accuracy in the very weak features group. The Root Square Mean Error (RMSE) for each feature selection shows the same pattern of results. [2] noted that the preparation of their data set required more than a single day. Rather than carrying out the calculations one after the other, we might use many processors to execute the calculations in parallel, which could potentially reduce both the preparation and prediction times. Add all the additional features to the model so that, instead of asking clients to provide a list, we may offer them the option to choose a district or another location to generate those maps with high temperatures. [7] employed a hundred-house data collection with multiple factors. Half of the data set was used for machine testing and the other half for machine training. The outcomes are very precise. Additionally, we tried it using various parameters. Training is simpler when PSO is not used. [13] worked with multiple linear regression, decision tree regression, and decision tree classifier—three of the most basic machine learning techniques. The machine learning programme Scikit-Learn is used to implement work. Both the availability and pricing of homes in the city can be predicted by users with the usage of this work. [8] predicted home prices using machine learning algorithms. We have described the methodical process for analysing the dataset. Following the entry of these feature sets into four algorithms, a CSV file containing the anticipated prices of homes was produced. [9] stated that a combination of these models must be used. While a high model complexity-based model yields a high bias (underfit), a linear model yields a high. According to [11], it is evident from running this experiment with a variety of machine learning algorithms that random forest and gradient boosted trees are working better, exhibiting higher accuracy percentages and lower error values. These algorithms perform well in terms of prediction when this experiment is compared to the label and the outcome obtained.

IV. PROPOSED WORK

The purpose of this system is to determine the price of a house by looking at the various features which are given as input by the user. These features are given to the ML model and based on how these features affect the label it gives out a prediction. This will be done by first searching for an appropriate dataset that suits the needs of the developer as well as the user. Furthermore, after finalizing the dataset, the dataset will go through the process known as data cleaning where all the data which is not needed will be eliminated and the raw data will be turned into a .csv file. Moreover, the data will go through data preprocessing where missing data will be handled and if needed label encoding will be done. Moreover, this will go through data transformation where it will be converted into a NumPy array so that it can finally be sent for training the model. While training various machine learning algorithms will be used to train the model their error rate will be extracted and consequently an algorithm and model will be finalized which can yield accurate predictions.

Users and companies will be able to log in and then fill a form about various attributes about their property that they want to predict the price of. Additionally, after a thorough selection of attributes, the form will be submitted. This data entered by the user will then go to the model and within seconds the user will be able to view the predicted price of the property that they put in.

4.1 Block Diagram of the System



The above block diagram is the traditional Machine Learning Approach. It consists of two sections: the training and the testing. The training has the following components: the label, input, feature extractor, and the machine learning algorithm. The testing section has the following components in it: the input, feature extractor, the regression model, and the output label.

Input: The input consists of data collected from various sources.

Feature Extractor: Only important features which affect the prediction results are kept. Other unnecessary attributes are discarded, like ID or name.

Features: After feature extraction only, some inputs are considered which largely contribute to the prediction of the model.

Machine Learning Algorithm: The ML Algorithm is the method by which an AI system performs its task, and is most commonly used to predict output values from given input values. Regression is one of the main processes of machine learning.

The Regression Model: The regression model consists of a set of machine-learning methods that allow us to predict a label variable (y) based on the values of one or more attribute/feature variables (x).

Briefly, the goal of a regression model is to build a mathematical equation that defines y as a function of the x variables.

Label: The label is the output obtained from the model after training.

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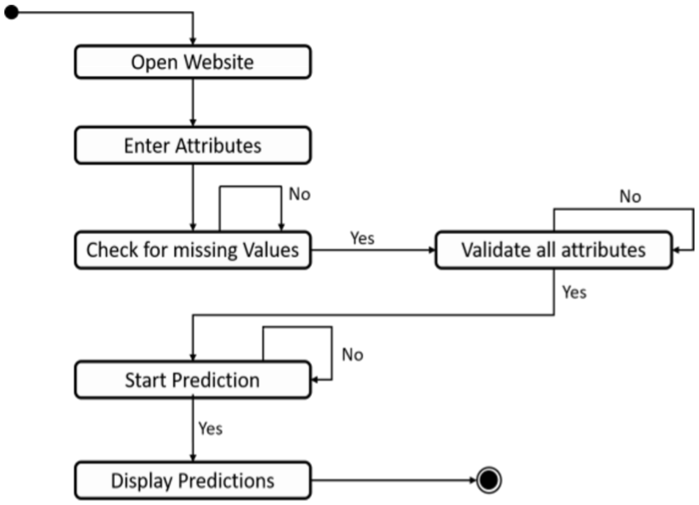
The data obtained from the dataset is given as a training input first and the relevant training features are extracted. These training features are preprocessed to get a normalized dataset and labeling of the data row is done. The result from the training dataset is fed to the machine learning algorithm. The result from the Machine Learning Algorithm is fed to the Regression model, thus producing a trained model or trained regressor. This trained regressor can take the new data that is the extracted feature from the test as input and predict its output label.

4.1 State Chart Diagram of the System



The user will open the website and enter all the features/attributes of the house they wish to predict the price for. Furthermore, after the user clicks submit attributes will be checked for null values then all the attributes will be validated to check if they are in the same data type as necessary. Finally, after all the conditions are satisfied the data will be sent for prediction and the predicted price will be displayed to the user on the website.

V. IMPLEMENTATION

5.1 Datasets

We have used two datasets in this paper where various existing machine learning algorithms are applied to the datasets for predicting prices.

A. The first dataset is from the UCI Machine Learning Repository which concerns housing values in the suburbs of Boston. This dataset was taken from the StatLib library which is maintained at Carnegie Mellon University. As this paper uses machine learning for price prediction, attribute variables are used to predict the label/price. The following table shows the set of attribute variables to develop the prediction model. This study uses 13 attributes as independent variables for predicting house prices.

Table 1: Attributes and label in the dataset (Boston)

Attributes	Description
CRIM	per capita crime rate by town
ZN	proportion of residential land zoned for lots over 25,000 sq.ft.
INDUS	proportion of non-retail business acres per town
CHAS	Charles River dummy variable (= 1 if tract bounds river; 0 otherwise)
NOX	nitric oxides concentration (parts per 10 million)
RM	average number of rooms per dwelling

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A. This data was scraped from publicly available results posted every week from Domain.com.au by Anthony Pino. We have used 13 major attributes affecting the price for prediction.

Table 2: Attributes and label in the dataset(Melbourne)

AGE	proportion of owner-occupied units built prior to 1940
DIS	weighted distances to five Boston employment centers
RAD	index of accessibility to radial highways
TAX	full-value property-tax rate per $10,000
PTRATIO	pupil-teacher ratio by town
B	1000(Bk - 0.63) ^2 where Bk is the proportion of blacks by town
LSTAT	% lower status of the population
MEDV	Median value of owner-occupied homes in $10,000's

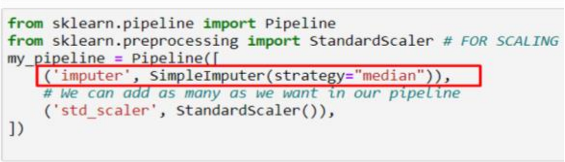
Attributes	Description
CouncilArea	Governing council for the area
Method	Method of sale
Regionname	General region
Rooms	Number of rooms:
Type	Type of house
Distance	Distance from CBD in Kilometres
Bedroom2	Scraped # of Bedrooms (from different source)
Bathroom	Number of Bathrooms
Car	Number of carspots
Landsize	Land Size in Metres
BuildingArea	Building Size in Metres
YearBuilt	Year the house was built
Propertycount	Number of properties that exist in th suburb.
Price	Price in Australian dollars

5.1 Data Cleaning

Handling Missing Values

The Boston dataset only had five missing values. However, the Melbourne dataset had a lot of missing values (in thousands). Dropping the null values was not an option since it negatively affected the accuracy. These null values were handled by replacing them with the median value of the column. The replacement was done by implementing the simple imputer function in the pipeline itself. So that any missing value in the future would be handled as soon as the data passes through the pipeline. Additionally, the Melbourne dataset had missing label/price values which had to be dropped for better results.

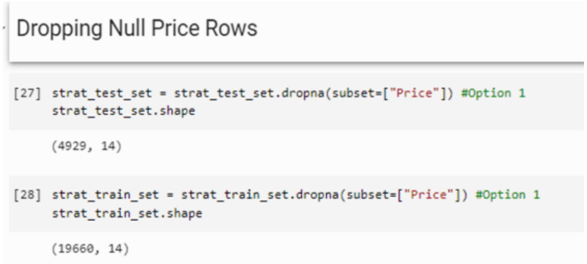
Creating a pipeline and dropping columns



```
from sklearn.pipeline import Pipeline
from sklearn.preprocessing import StandardScaler # FOR SCALING
my_pipeline = Pipeline([
    ('imputer', SimpleImputer(strategy="median")),
    # We can add as many as we want in our pipeline
    ('std_scaler', StandardScaler()),
])
```

Figure 5.1.c Simple Imputer Code Snippet

We have dropped a few columns like ID or seller_info since they didn't have any effect on the final predictions.



Dropping Null Price Rows

```
[27] strat_test_set = strat_test_set.dropna(subset=["Price"]) #Option 1
     strat_test_set.shape

     (4929, 14)

[28] strat_train_set = strat_train_set.dropna(subset=["Price"]) #Option 1
     strat_train_set.shape

     (19660, 14)
```

Figure 5.1.d Dropping Null Price rows from Melbourne dataset

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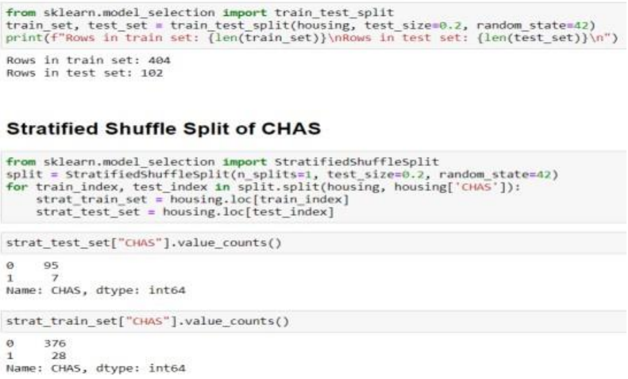
5.2 Data Preprocessing

Train and Test Split
We have split the dataset into two sets i.e. the Training set and the Testing set. Training set consists of 80% of the dataset and the testing set has 20% of the dataset. We had columns with only two distinct values and wanted to make sure that the splitting should split these values in equal proportions. Therefore, we used a stratified shuffle split for train test splitting for better results.

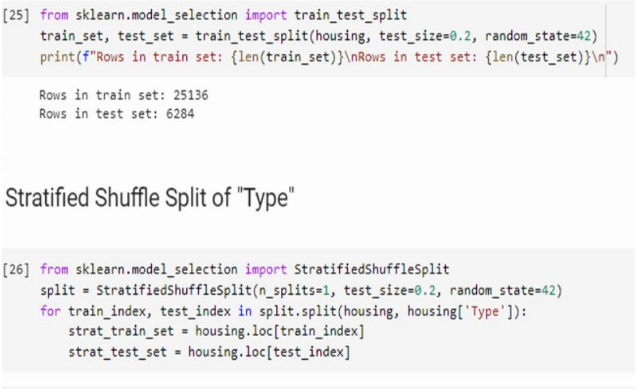


```
from sklearn.model_selection import train_test_split
train_set, test_set = train_test_split(housing, test_size=0.2, random_state=42)
print(f"Rows in train set: {len(train_set)}\nRows in test set: {len(test_set)}\n")

Rows in train set: 404
Rows in test set: 102
```

Stratified Shuffle Split of CHAS

```
from sklearn.model_selection import StratifiedShuffleSplit
split = StratifiedShuffleSplit(n_splits=1, test_size=0.2, random_state=42)
for train_index, test_index in split.split(housing, housing['CHAS']):
    strat_train_set = housing.loc[train_index]
    strat_test_set = housing.loc[test_index]

strat_test_set["CHAS"].value_counts()

0    95
1     7
Name: CHAS, dtype: int64

strat_train_set["CHAS"].value_counts()

0    376
1     28
Name: CHAS, dtype: int64
```

Figure 5.2.a Stratified Shuffle Split in Boston dataset



```
[25] from sklearn.model_selection import train_test_split
     train_set, test_set = train_test_split(housing, test_size=0.2, random_state=42)
     print(f"Rows in train set: {len(train_set)}\nRows in test set: {len(test_set)}\n")

     Rows in train set: 25136
     Rows in test set: 6284
```

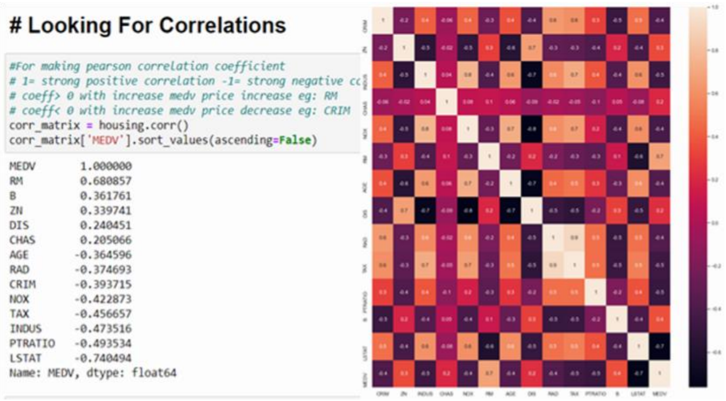
Stratified Shuffle Split of "Type"

```
[26] from sklearn.model_selection import StratifiedShuffleSplit
     split = StratifiedShuffleSplit(n_splits=1, test_size=0.2, random_state=42)
     for train_index, test_index in split.split(housing, housing['Type']):
         strat_train_set = housing.loc[train_index]
         strat_test_set = housing.loc[test_index]
```

Figure 5.2.b Stratified Shuffle Split in Melbourne dataset

5.3 Correlation and Data Visualization

Correlation between all attributes and the label:



Looking For Correlations

```
#For making pearson correlation coefficient
# 1= strong positive correlation -1= strong negative cc
# coeff> 0 with increase medv price increase eg: RM
# coeff< 0 with increase medv price decrease eg: CRIM
corr_matrix = housing.corr()
corr_matrix['MEDV'].sort_values(ascending=False)

MEDV       1.000000
RM         0.680857
B          0.361761
ZN         0.339741
DIS        0.240451
CHAS       0.205066
AGE       -0.364596
RAD       -0.374693
CRIM      -0.393715
NOX       -0.422873
TAX       -0.456657
INDUS     -0.473516
PTRATIO   -0.493534
LSTAT     -0.740494
Name: MEDV, dtype: float64
```

Figure 5.3.a Correlation heat map between all attributes and the label (Boston)

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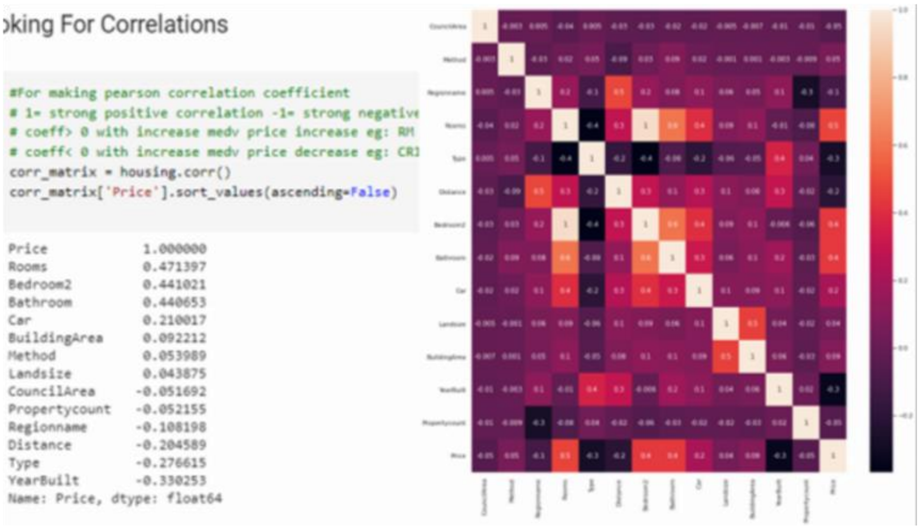
From the above figure, we can see that RM (No of rooms) was highly positively correlated followed by B and LSTAT and PTRATIO were the two most negatively correlated attributes. This means that if the value of RM or B has increased the price will increase and if the PTRATIO of LSTAT were to increase the price would decrease.



ɔking For Correlations

```
#For making pearson correlation coefficient
# 1= strong positive correlation -1= strong negative
# coeff> 0 with increase medv price increase eg: RM
# coeff< 0 with increase medv price decrease eg: CRI
corr_matrix = housing.corr()
corr_matrix['Price'].sort_values(ascending=False)
```

```
Price            1.000000
Rooms            0.471397
Bedroom2         0.441021
Bathroom         0.440653
Car              0.210017
BuildingArea     0.092212
Method           0.053989
Landsize         0.043875
CouncilArea     -0.051692
Propertycount   -0.052155
Regionname      -0.108198
Distance        -0.204589
Type            -0.276615
YearBuilt       -0.330253
Name: Price, dtype: float64
```

Figure 5.3.b Correlation heat map between all attributes and the label
(Melbourne)

From the above figure, we can see that the attribute Rooms were highly positively correlated followed by Bedrooms and Type and YearBuilt were the two most negatively correlated attributes. This means that if the value of Rooms or Bedrooms were increased then the Price will increase and if the Type of YearBuilt were to increase the price would decrease.

Determining the relationship between Label and one random Attribute:

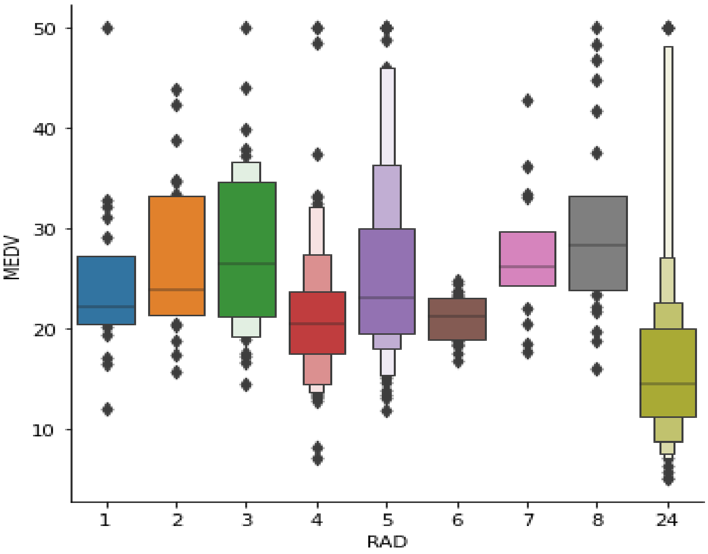


Figure 5.3.c MEDV(price) wrt RAD

For a maximum of the Distance’s the inner 50% of the price was between 15 to 35 and the median hitting mostly at 20. However, for RAD 21 the price experienced a downfall as the distance from the highway increased the price got lower. Median staying at just 15.

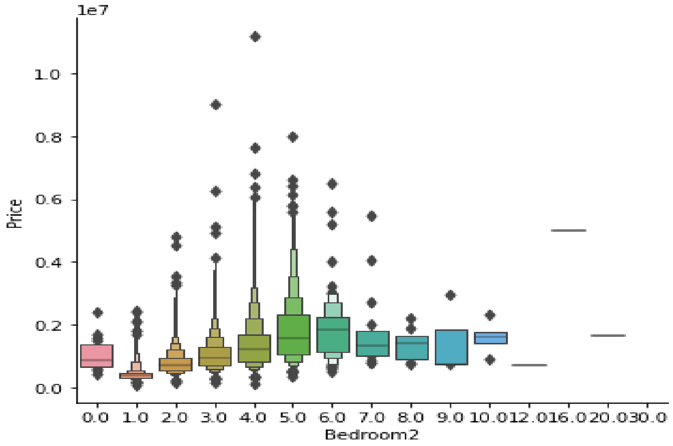


Figure 5.3.d Price wrt Bedroom count

It was observed that increasing bedroom count did not affect the price that much and surprisingly houses with several bedrooms between 3 to 6 topped the chart rather than the houses which had 8 to 30 bedrooms. And a house with 4 bedrooms had the highest price as compared to others.

VI. RESULTS

The following two tables show the RMSE Scores (mean and standard deviation) and Mean Cross-Validation Scores of the Boston dataset for four different machine learning algorithms and the Melbourne dataset for five different machine learning algorithms. Using these tables, we can infer the accuracy of all the algorithms for both the datasets and determine the best suitable algorithm for price prediction.

Boston Dataset			
Algorithm	**RMSE mean**	**RMSE Std. Dev.**	**Mean CrossVal Score**
XGBoost	3.06	0.75	0.88
Random Forest	3.38	0.76	0.85
Decision Tree	4.189	0.848	0.76
Linear Regression	4.22	0.75	0.69

Table 6.1 RMSE and Mean CrossVal of Boston Dataset

In general, the best accuracy was provided by the XGBoost Regression machine learning algorithm closely followed by Random Forest regression algorithm and Decision tree coming at the third place with a sizable difference. Additionally, the Linear Regression algorithm coming at last with a huge gap if compared to XGBoost. All these model predictions were checked for overfitting by evaluating these values using the cross-validation technique. So, these scores are extremely accurate.

Melbourne Dataset			
Algorithm	**RMSE mean**	**RMSE Std. Dev.**	**Mean CrossVal Score**
XGBoost	299880.4	23019.5	0.79
Random Forest	312347.6	19880.3	0.76
Gradient Boosting	342911.4	26544.5	0.73
Decision Tree	421026.9	15907.3	0.6
Linear Regression	519029.1	97954.6	0.38

Table 6.2 RMSE and Mean CrossVal of Melbourne Dataset

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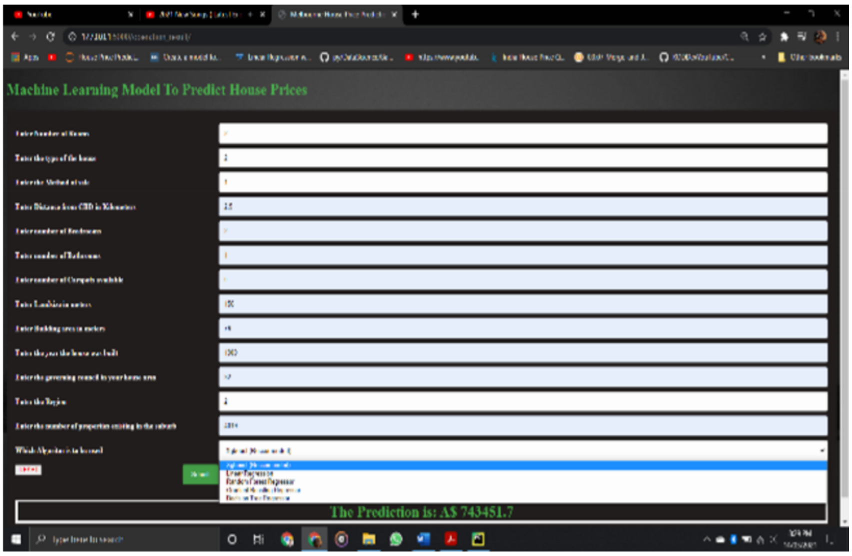
In general, the best accuracy was provided by the XGBoost Regression machine learning algorithm closely followed by Random Forest regression algorithm and Gradient Boosting algorithm coming at the third place with a slight difference. Additionally, the decision tree algorithm came fourth with a sizable difference in scores, and finally, the Linear Regression algorithm came last with a huge gap if compared to XGBoost. All these model predictions were checked for overfitting by evaluating these values using the cross-validation technique. So, these scores are extremely accurate.

6.1 Price Predicting Website



Machine Learning Model To Predict House Prices

Enter Number of Rooms	[illegible]
Enter the type of the house	2
Enter the Method of sale	1
Enter Distance from CBD in Kilometres	2.5
Enter number of Bedrooms	[illegible]
Enter number of Bathrooms	1
Enter number of Carspots available	[illegible]
Enter Landsize in metres	[illegible]
Enter Building area in metres	[illegible]
Enter the year the house was built	[illegible]
Enter the governing council in your house area	[illegible]
Enter the Region	2
Enter the number of properties existing in the suburb	[illegible]
Which Algorithm is to be used	[illegible]

The Prediction is: A$ 743451.7

Figure 6.1

This is our take at developing a real-life solution for a house price prediction query. By developing a clean and simple UI, individuals with little to no experience will easily be able to predict prices for their dream house. This website was built on Flask technology and has a form where users can enter all the features of their house and predict prices as per their convenience. Additionally, the website provides users with the option of using the various machine learning algorithms for prediction (the best one comes auto-selected).

VII. CONCLUSION AND FUTURE SCOPE

Buying your own house is what every human wish for. Using this proposed model, we want people to buy houses and real estate at their rightful prices and want to ensure that they don't get tricked by sketchy agents who just are after their money. Additionally, this model will also help Big companies by giving accurate predictions for them to set the pricing and save them from a lot of hassle and save a lot of precious time and money. Correct real estate prices are the essence of the market and we want to ensure that by using this model.

The system is apt enough in training itself and in predicting the prices from the raw data provided to it. After going through several research papers and numerous blogs and articles, a set of algorithms were selected which were suitable in applying on both the datasets of the model. After multiple testing and training sessions, it was determined that the XGBoost Algorithm showed the best result amongst the rest of the algorithms. The system was potent enough for Predicting the prices of different houses with various features and was able to handle large sums of data. The system is quite user-friendly and time-saving.

The supplementary feature that can be added to our proposed system is to avail users of a full-fledged user interface so there can be multiple functionalities for users to use with the ML model for numerous locations. Also, an Amazon EC2 connection will take the system even further and increase the ease of use. Lastly, developing a well-integrated web application that can predict prices whenever users want it to will complete the project.

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