

House Price Prediction Using Texture and Visual Features

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Abstract- Real estate sector has been growing at a rate never seen before. For this sector, a key role is played by the pricing of the property. Gone are the days when the price of the property was based on whims and fancies of the real estate dealers. Machine learning has numerous applications in the domain of real estate, and one of the most popular ones is predicting house prices. The application of machine learning in house price prediction involves training a model on a dataset that includes a variety of visual and texture features related to the property. The model is then used to predict the price of a new property based on its features.

This paper successfully explores machine learning based house price prediction. The methodology followed was to first use data sets to train the model. Later, using correlation-based hybrid GA-reinforcement strategy, a suitable set of features has been selected. In the end, these features are applied to a XG boost regressor to get results. The accuracies are compared with the cases of without feature selection of different regressors. This algorithm, if successfully deployed will be beneficial to both sellers and buyers, because it sets a data-based benchmarking for pricing the property.

Indexed Terms- GA-reinforcement strategy, XG boost regressor

I. Introduction

The visual and textural features of house price prediction images can be very important in predicting the price of a house. Visual features such as the size, shape, and color of a house can give an indication of the value of the house. Textural features such as the type of material used on the exterior or interior can also be important. In addition, the overall design of the house, such as whether it is modern or traditional, can also be a factor in predicting price. The size of a home can be an important factor in determining its price. Homes that are larger, have more rooms, and are in desirable neighborhoods tend to cost more than smaller homes. The shape of the house can also be a factor, as houses with unusual shapes can be more expensive. The color of a home can also be an important factor in determining price. Homes painted in bright colors are considered more attractive and may cost more than homes painted in more muted colors. Finally, the location of the home can be an important factor in its price. Homes in more desirable areas can cost more than homes in less desirable areas. The view from the house can also be a factor, as houses with better views can cost more than houses with poorer views.

Pricing plays the most important role in the real estate sector. It can be a make-or-break factor when it comes to closing a deal. Accurate price prediction of a property is of great importance in the real estate domain for several reasons:

1. Helps in making informed decisions
2. Maximizes profit
3. Reduces time on the market
4. Improves customer satisfaction
5. Increases credibility.

With no data-backed methodology currently existing to accurately formulate a benchmark, machine learning comes handy for such purposes. By giving a dataset of images of the interior and exterior of houses and properties, a model can be trained to give prediction of the prices based on the dataset. This methodology involves multiple steps, explained further in the publication.

II. Literature Survey

To build a methodology of our own for the price prediction, an analysis has been done on different ML algorithms.

Real estate valuation has been an area of research interest for several years. Traditional real estate valuation models have primarily relied on features such as location, property size, and amenities to predict house prices. However, recent studies have explored the use of visual and textual features to enhance the accuracy of real estate valuation models.

Huang et al. (2018) proposed a deep learning-based house price estimation model that uses visual and textual features. The model achieved better accuracy compared to traditional models that use only textual features. Li et al. (2019) conducted a systematic literature review on predicting house prices using machine learning techniques. The review found that machine learning models such as decision trees, support vector machines, and artificial neural networks have been widely used in the literature.

Madhukar and Singh (2019) proposed an ensemble learning-based model that combined multiple machine learning models to predict house prices. The model achieved high accuracy and outperformed several other models. Srinivasan and Cao (2020) proposed a hybrid deep learning and XGBoost model for house price prediction. The model achieved better accuracy compared to traditional machine learning models.

Yang et al. (2019) conducted a review of traditional and intelligent techniques for real estate appraisal. The review highlighted the importance of incorporating additional data sources such as visual and textual features to enhance the accuracy of real estate valuation models.

Anand Rawool in his paper “House Price Prediction Using Machine Learning” uses algorithms like Linear Regression, Decision Tree, Regression, K-Means Regression and Random Forest Regression. The work was done in 3 steps – 1. Collection of data, then data pre-processing and then training the model using Random Forest Regression. Out of the data set, he used 80% of the data for training, and the remaining for testing. He saw best results with Linear regression, where Standard deviation is just 0.75. The other methods used were Linear Regression, Decision Tree and K-Means.

Ayush Verma in his IEEE publication “House Price Prediction Using Machine Learning and Neural Networks” used weighted mean of various regression techniques to minimize the deviation via each algorithm. He also proposed to use real-time neighborhood details using Google maps to get exact real-

world valuations.

Alisha Kuvalekar in her paper titled “House Price Forecasting Using Machine Learning” used decision tree regressor and machine learning. Her conclusion was that decision tree regressor provided the highest accuracy in terms of prediction. The accuracy was close to 89% with the given model.

G. Naga Satish, on the contrary had a different approach in his paper titled “House Price Prediction Using Machine Learning”. He utilized lasso regression process and neural system, housing cost prediction to get the required results. The Lasso regression was 76% accurate, and the later by 91%. Overall, the literature suggested that incorporating visual and textual features can enhance the accuracy of real estate valuation models. Machine learning techniques such as deep learning, XGBoost, and ensemble learning have been shown to be effective in predicting house prices. The proposed approach in this research paper has built on this literature by using XGBoost and GA-RL strategy to enhance the accuracy of the model.

III. Methodology & Implementation

In this proposed system the focus was to predict house price using machine learning models through google images datasets. The methodology is as explained below

A. Extracting visual and texture features of house price prediction images dataset:

Google images datasets has been taken from open-source platforms to extract visual and textural features from the image's dataset. The focus was mainly on the most prominent visual cues like exterior quality, size of the house, etc. This data set has been taken from royalty free google dataset repository.



Image 3.1: Sample Data

B. Selecting suitable set of features using correlation-based hybrid GA-reinforcement learning strategy

The correlation-based hybrid GA-reinforcement learning strategy has been used to select the best features out of the given data set. Correlation-based hybrid GA-reinforcement learning strategy is a technique used in the field of artificial intelligence and machine learning to optimize the performance of a system or agent. The reason of choosing this strategy was to utilize the best of both Genetic algorithms and ensure that reinforced learning was utilized in the best possible way. Other models are not expected to be the best choices for this scenario due to low convergence expectations.

This strategy combines two popular techniques: genetic algorithms (GA) and reinforcement learning (RL). Genetic algorithms are a type of optimization algorithm that is inspired by the process of natural selection. They are used to search for the best set of parameters or features that maximize a given objective function. Reinforcement learning, on the other hand, is a

type of machine learning that enables an agent to learn by trial-and-error in an environment. In a correlation-based hybrid GA-RL strategy, the GA is used to optimize the hyperparameters of a reinforcement learning algorithm. This is done by encoding the hyperparameters as part of the chromosome in the genetic algorithm, and then evolving the population of chromosomes over several generations to find the best set of hyperparameters. The RL algorithm is then trained using the optimized hyperparameters.

One of the key features of a correlation-based hybrid GA-RL strategy is the use of correlation-based mutation operators in the GA. These operators exploit the correlation between the hyperparameters and the performance of the RL algorithm to guide the search towards better solutions.

The flow of GA-RL algorithm is explained in the diagram below.

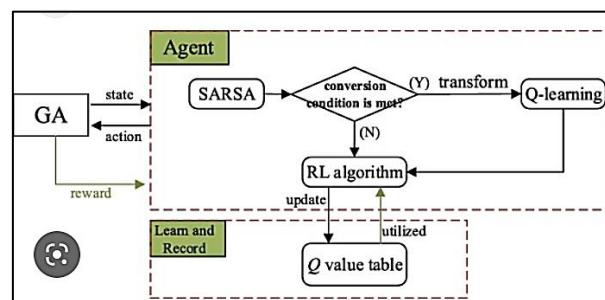


Image 3.2: GA-RL Strategy

A self-learning genetic algorithm (SLGA) is shown above. Here, genetic algorithm (GA) is adopted as the basic optimization method and its key parameters are intelligently adjusted based on reinforcement learning (RL). Firstly, the self-learning model is analyzed and constructed in SLGA, SARSA algorithm and Q-Learning algorithm are applied as the learning methods at initial and later stages of optimization, respectively, and the conversion condition is designed.

The combination of Genetic Algorithms (GA) and Reinforcement Learning (RL) can have several advantages in machine learning. Firstly, it is Improved Exploration. RL algorithms can sometimes get stuck in local optima and fail to explore other possible solutions. GA can help overcome this problem by providing a mechanism for exploring a broader range of potential solutions.

Secondly, Increased Robustness. GA-RL strategies can produce more robust models that can generalize better to new data. This is because GA-RL can produce models that are less sensitive to changes in the input data, which can improve the overall performance of the model.

Third being Better Scalability: GA-RL can handle high-dimensional state spaces more efficiently than traditional RL algorithms. GA can reduce the number of possible solutions to explore, and thus make it easier for RL algorithms to optimize the policy.

Hence, overall, GA-RL can converge to optimal solutions faster than traditional RL algorithms. This is because GA can identify promising solutions quickly, and RL can fine-tune these solutions to maximize the reward. The choice of GA-RL strategy was obvious

because of the above reason. Since this was a high-dimension state space, the convergence time was very critical for such scenario.

C. Apply these features to a XG boost regressor

XGBoost (Extreme Gradient Boosting) is a popular open-source library used for gradient boosting algorithms. XGBoost Regressor is a machine learning model that uses the XGBoost library to perform regression tasks. Gradient Boosting is a popular ensemble learning technique in machine learning, where multiple models are trained sequentially to improve the accuracy of the final model. In gradient boosting, each new model learns from the mistakes of the previous model and tries to correct them.

XGBoost Regressor works by building a series of decision trees, where each tree is trained to predict the residual error of the previous tree. The final prediction is the sum of the predictions of all the trees. The algorithm optimizes a loss function by minimizing the difference between the predicted and actual values.

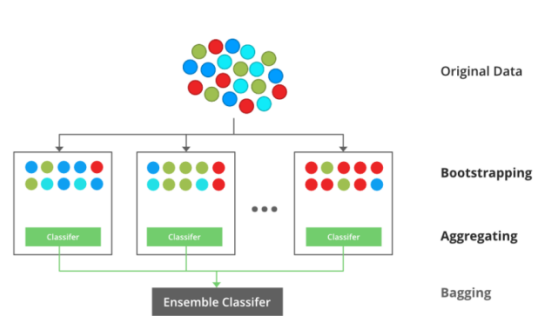


Image 3.3: XGBoost Algorithm

The reason of choosing this regressor was the benefits that come attached to it. Some of the benefits of using XGBoost Regressor are (1) High performance: XGBoost Regressor is known for its speed and efficiency, making it a popular choice for large datasets. (2) Feature importance: XGBoost Regressor provides a way to rank the importance of features in a dataset, which can be useful for feature selection and feature engineering. (3) Regularization: XGBoost Regressor provides regularization parameters to prevent overfitting, which can help to improve the generalization performance of the model.

D. Implementation of XG Boost Model:

The formulas that help in making the XGBoost Tree are as follows:

(1) To calculate similarity score:

$$\text{Similarity Score} = (\text{Sum of residuals})^2 / \text{Number of residuals} + \text{lambda}$$

(2) To calculate the gain:

$$\text{Gain} = \text{Left tree (similarity score)} + \text{Right (similarity score)} - \text{Root (similarity score)}$$

(3) Prune tree:

$$\text{Gain} - \text{Gamma}$$

(4) Output values:

$$\text{Output value} = \text{Sum of residuals} / \text{Number of residuals} + \text{lambda}$$

XG Boost starts its initial calculation by 0.5.

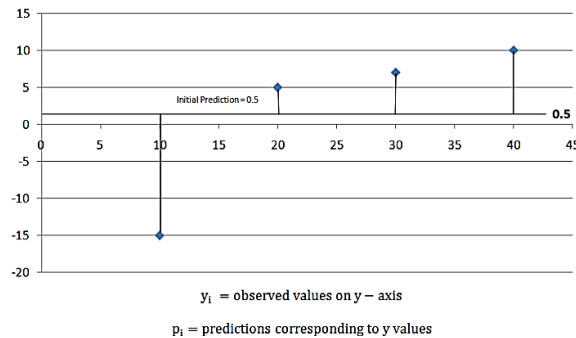


Image 3.4: Prediction plot

E. Fitting the inaccuracies

To find the quality of prediction, Loss function was calculated using below formula, which comes out to be 196.5 in our case.

$$L(y_i, p_i) = \frac{1}{2}(y_i - p_i)^2$$

In general,

$$\sum_{i=1}^n L(y_i, p_i) = \frac{1}{2}(y_i - p_i)^2$$

For the given example training set:

$$\sum_{i=1}^n L(y_i, p_i) = \frac{1}{2}(-15 - 0.5)^2 + \frac{1}{2}(5 - 0.5)^2 + \frac{1}{2}(7 - 0.5)^2 + \frac{1}{2}(10 - 0.5)^2 = 196.5$$

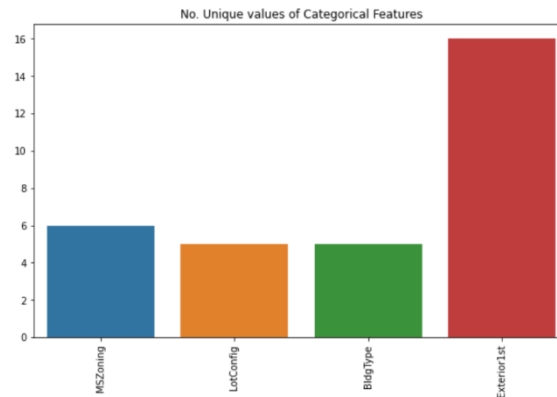
Image 3.5: Loss function for the data set

For understanding the improvements, Loss function was used to calculate the Loss. With improvement in the data set, the loss function should also improve.

IV. Results

Training: The strategy has been trained with 80% data available and the remaining 20% datasets are used for testing the accuracy.

Categorization: Categorization of data: The categorization of data was done as per interior and exterior features. The exterior features had 16 categories and other features have 6 unique categories.



XGBoost: The cost vs time curve for XGBoost Algorithm was found to be as below:

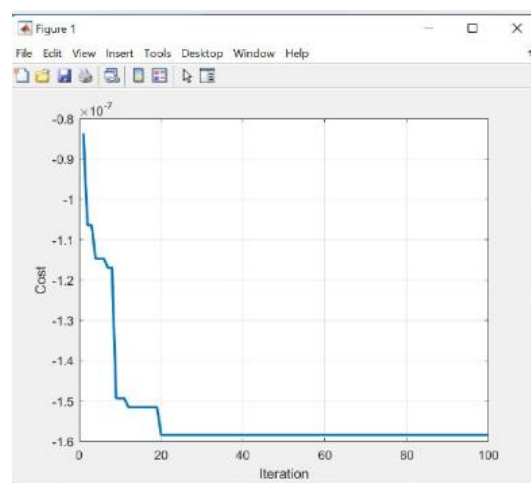


Image 4.1: Cost vs iteration curve

This curve depicts that the cost function is coming down as the number of iterations were increased. In simple language, the model can adapt and learn from the previous data, and the cost of each iteration is reducing with each subsequent run.

RMSE: The Root mean square error was found to be 0.01as seen in the below result snapshot.

```
rmse =
    0.0100

rmse =
    0.0100
```

Image 4.2: RMSE after 1000 iterations

Accuracy: 80% of the dataset was used to train the GA-RL and remaining 20% to test the

datasets for accuracy. The XGBoost algorithm backed by GA-RL strategy was 86.1235% accurate, as seen using the below python-based algorithm.

```
from sklearn import svm
from sklearn.svm import SVC
from sklearn.metrics import mean_absolute_percentage_error
```

```
Model_SVR = svm.SVR()
Model_SVR.fit(X_train, Y_train)
Y_pred=model_SVR.predict(X_valid)
```

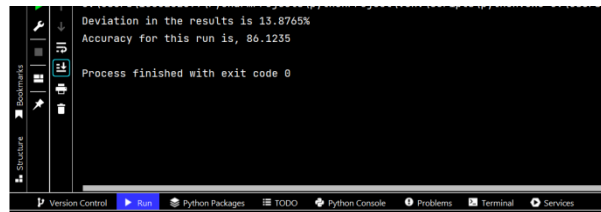


Image 4.3: Results snapshot

Comparison: The results as compared to other training algorithms are as tabulated below:

Final RMSE=	Mean	Standard Deviation
2.9131988953		
Linear Regression	4.221894675	0.752030492
Decision Tree	4.189504504	0.848096620
K-Means	21.91834139	2.115566025
Random Forest	3.494650261	0.762041223

Table 4.1: RMSE comparison with others

It is seen that the RMSE in all the cases is worst than the RMSE in the work implemented. Hence, we can conclude that GA-RL strategy combined with XG-Boost is the best way forward to do an accurate price prediction.

This accuracy can be further improved with a cleaner data set and combining other upcoming strategies in the machine learning space in future.

V. Real World Applications & Impact

House price prediction is an important area of research and analysis for several reasons:

1. Real estate is a significant component of the economy: The real estate sector is a vital contributor to the economy. The value of residential real estate is a critical indicator of economic health. Therefore, predicting house prices accurately can help businesses and policymakers make informed decisions.
2. Investment decisions: House price prediction is vital for making informed decisions about real estate investment. Investors need to know the current and future value of a property to determine whether it is a sound investment or not.

3. **Mortgage lending:** Mortgage lenders rely heavily on house price predictions to determine the loan amount and interest rates for borrowers. Accurate predictions help lenders mitigate risk and offer competitive rates.
4. **Government policies:** Governments need accurate predictions to design effective policies that regulate the real estate market, promote economic growth, and ensure the availability of affordable housing.
5. **Homeowners:** Homeowners need to know the value of their properties, whether they plan to sell or not. Accurate predictions can help homeowners make informed decisions about refinancing, renovations, and more.

VI. Future Scope

The paper has several future research directions, including:

1. **Improving the accuracy of the model:** While the results of the research paper are promising, there is still room for improvement in the accuracy of the model. Future research could explore the use of other machine learning techniques or the incorporation of additional features to further improve the accuracy of the model.
2. **Generalization to other real estate markets:** The research paper focuses on the prediction of house prices in a specific market. Future research could explore the generalization of the model to other real estate markets, including international markets, to evaluate the model's effectiveness in different contexts.
3. **Incorporation of additional data sources:** The research paper uses texture and visual features to predict house prices. Future research could explore the use of other data sources, such as demographic data, neighborhood characteristics, or historical sales data, to improve the accuracy of the model.
4. **Application to other real estate tasks:** The research paper focuses on the prediction of house prices. Future research could explore the application of the model to other real estate tasks, such as the prediction of rental prices, the identification of undervalued properties, or the estimation of renovation costs.

VII. Conclusion

In conclusion, the research paper titled "House Price Prediction Using Texture and Visual Features" proposed a novel approach to predict house prices using texture and visual features. The proposed model used two machine learning techniques, XGBoost and GA-RL, to create an accurate model for house price prediction.

The proposed approach has the potential to be extended to other real estate tasks and incorporating additional data sources could further enhance the accuracy of the model. Overall, the research paper provides a valuable contribution to the field of real estate valuation and provides a promising direction for future research.

Moreover, the proposed approach provides an efficient solution for real estate investors, developers, and homeowners to predict house prices accurately. Accurate prediction of house prices can enable real estate stakeholders to make informed decisions regarding property investments and sales, leading to better financial outcomes. The proposed approach's ability to use texture and visual features to predict house prices distinguishes it from other existing

models that rely on traditional features such as location, size, and amenities. Additionally, the use of GA-RL strategy to optimize the model parameters further enhances the accuracy of the model. Therefore, the proposed approach can be a useful tool for real estate valuation, especially in markets with limited availability of traditional data sources.

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