Available at www.ijsred.com

RESEARCH ARTICLE

OPEN ACCESS

Analysis and Optimization of Room Rent in Urban Areas Using ML

Bhuneshwari Sahu*, Dipti Sahu**, Nidhi Ramteke***, Rajshekhar Diwakar****, Prof. Aparna Pandey****

Abstract:

In urban areas, the cost of renting rooms can vary significantly based on various factors such as location, amenities, and local market conditions. Predicting and optimizing room rent using machine learning (ML) techniques has gained significant attention due to its potential to provide valuable insights for both tenants and landlords. This review paper explores the current state of research in predictive analysis and optimization of room rent in urban areas using ML. We discuss methodologies, datasets, challenges, and future directions in this emerging field. This study analyzes rent data from Raipur City in India with multiple variables, including size, furnishing status, and the number of bathrooms, bedrooms, halls, and kitchens, Nearby convenient places like grocery stores, hospitals, markets, etc., and creates a prediction model based on the data. The main analytical methods used are Machine Learning and logarithmic transformation. This study also includes a general factor analysis based on the data. The results suggest that this model is reasonably accurate for reference uses, but needs further improvements if it is to be used commercially.

Keywords —Machine Learning, prediction model, logarithmic transformation.

I. INTRODUCTION

Rental prices in urban areas are influenced by a complex interplay of factors including location, neighborhood characteristics, transportation accessibility, and economic trends. Traditional methods of determining rental prices often rely on subjective assessments or historical trends. ML algorithms offer a data-driven approach to analyze these factors and predict rental prices more accurately. Predictive Analysis and Optimization of Room Rent can be done by using multiple prediction models (Machine Learning Models) such as support vector regression, artificial neural network, and more. There are many benefits that home buyers, property investors, and house builders can reap from the house-price model. This model

will provide a lot of information and knowledge to home buyers, property investors, and house builders, such as the valuation of house prices in the present market, which will help them determine house prices. Meanwhile, this model can help potential buyers decide the characteristics of a house they want according to their budget. Previous studies focused on analyzing the attributes that affect house prices and predicting house prices based on the model of machine learning separately. However, this article combines both predicting house prices and attributes. In this article, the literature review focuses on predicting areas for room rent based on the model of machine learning as well as analyzing attributes primarily used in previous studies that affect house prices. This paper was arranged as follows: the first section summarizes the overall of

International Journal of Scientific Research and Engineering Development-- Volume 7 Issue 2, Mar-Apr 2024 Available at www.ijsred.com

this study. The second section describes the common attributes used in the prediction of the area of room rent and price around the world. It was followed by a brief discussion of the machine learning model used in a previous study to predict house prices. In the next section, the comprehensive effects of the current house price and area prediction model are addressed.

II. METHODOLOGIES

Several ML techniques have been employed to predict and optimize room rent:

- Regression Models: Linear regression, polynomial regression, and ensemble methods like random forests have been used to model the relationship between room rent and predictors such as location, property size, and local amenities.
- Neural Networks: Deep learning models such as neural networks can capture complex patterns in rental data, although they require large datasets and computational resources.
- Clustering and Segmentation: Unsupervised learning techniques like clustering can group neighborhoods or properties based on similar rent profiles. Time Series Analysis: For understanding rent trends over time, time series forecasting methods can be applied.

It involved the application of machine learning techniques to develop predictive models for apartment rental price forecasting.

Model Selection and Evaluation:

A diverse set of machine learning algorithms was tested and evaluated to identify the most effective model for rental price prediction. The model selection process included:

- Splitting the dataset into training and test sets (70/30 split) to facilitate model training and evaluation
- Implementing a wide range of algorithms such as Random Forest, Gradient Boosting, Support Vector Machines (SVM), and Neural Networks Using cross-validation

techniques (e.g., k-fold cross-validation) to assess model performance and generalization

• Model evaluation metrics such as accuracy, mean squared error and area under the receiver operating characteristic curve (AUC-ROC) were used to compare and select the best-performing model.

Hyperparameter Tuning and Optimization:

Hyperparameters of selected models were finetuned using techniques like grid search or random search to optimize model performance metrics. Hyperparameter tuning involved:

- Iteratively adjusting model parameters based on cross-validation results
- Balancing model complexity and generalization using regularization techniques (e.g., L1/L2 regularization)

Interpretation and Analysis of Model Results:

The interpretability of machine learning models was crucial for understanding the factors influencing rental prices and deriving actionable insights. Methods for interpreting model results included:

- Feature importance analysis using SHAP (SHapley Additive exPlanations) values
- Visualizing decision boundaries and model predictions
- Analyzing model errors and limitations to inform future model enhancements

The systematic application of machine learning techniques enabled the development of accurate and interpretable predictive models for apartment rental price forecasting, providing valuable insights into market dynamics and influencing factors in Vilnius.

III. ATTRIBUTES

House price prediction can be divided into two categories, first by focusing on house characteristics, and secondly by focusing on the model used in house price prediction. Many researchers have produced a house price prediction

International Journal of Scientific Research and Engineering Development-- Volume 7 Issue 2, Mar-Apr 2024 Available at www.ijsred.com

model, including. The research undertaken analyzes the existing housing prices in Jakarta, Indonesia using the conceptual model and questionnaires. Based on the results, the attributes or factors affecting the house price differ for each house construction in Jakarta, therefore accepting the validity of this analysis as the main purpose of this research is to classify the factors or attributes affecting the house price.

- A. Locational: Location is considered to be the most significant feature of house price determination in his study also observed the significance of location attributes in deciding house price. The location of the property was classified in a fixed locational attribute. All of these studies point to the close association between locational attributes such as distance from the closest shopping center, or position offering views of hills or shore, and house price variations.
- B. Structural: Another significant feature influencing the house price is structural structure or some research has listed it as physical attributes. Structural characteristics are features that people may identify, number of bedrooms whether and bathrooms, floor space, or garage and patio. These structural attributes, often offered by house builders or developers to attract therefore potential buyers, meet the potential buyers' wishes.
- C. Neighborhood: Neighborhood qualities can be included in deciding house prices. According to, the efficiency of public education, community social status, and proximity to shopping malls typically improve the worth of a property. There is a substantial rise in house prices from the fifth-class suburban community to affluent neighborhoods as predicted.

IV. RESULTS AND DISCUSSION

Evaluation of Machine Learning Models: The comparative analysis of machine learning models for predicting apartment rental prices revealed distinct variations in performance across the different algorithms. The application of accuracy, mean squared error (MSE), and area under the receiver operating characteristic curve (AUC-ROC) metrics provided a comprehensive understanding of each model's predictive capabilities within the dataset comprising apartment listings from May to August 2020. The Random Forest algorithm emerged as a particularly robust model, characterized by high accuracy and low MSE, underscoring its efficacy in predicting rental prices Conversely, Gradient accurately. Boosting distinguished itself by adeptly capturing complex patterns within the rental data, suggesting its superiority in managing nonlinear relationships. Support Vector Machines (SVM) were noted for their competitive performance, especially in classifying apartments into distinct rental price categories. Neural Networks, with their deep learning prowess, exhibited potential, albeit constrained by the considerable computational resources required for training.

Impact of Feature Selection: Feature importance analysis elucidated the significance of apartment size, location, number of rooms, construction year, and proximity to amenities as critical determinants of rental prices. The SHAP value-based analysis offered insights into the contribution of each feature, with spatial trends and amenity proximity being particularly influential factors. These findings reinforce the notion that prime zones, newer accessibility construction. and to urban conveniences are perceived as high-value attributes in the rental market.

Market Dynamics: The seasonal patterns within rental prices were unmistakable, with a notable peak during the summer months and a dip in the winter. The COVID-19 pandemic further complicated these trends, introducing volatility in rental prices that correlated with the evolving supply and demand dynamics as quarantine measures impacted the market.

International Journal of Scientific Research and Engineering Development--- Volume 7 Issue 2, Mar-Apr 2024 Available at www.ijsred.com

Strategic Implications: For stakeholders in the real estate sector, these models serve as a tool to inform strategic decision-making. Property investors can utilize predictive models to identify promising investment opportunities and maximize rental vields. Developers, on the other hand, can align their pricing strategies with current market trends, ensuring competitiveness and market appeal. Renters, too, stand to gain from these insights, as they can make more informed decisions regarding property selection and leasing negotiations.

Considerations for Future **Research:** The limitations presented by data availability and quality point to the need for a cautious interpretation of the current study's results. The potential for improved model performance through enhanced data collection and augmentation techniques presents a compelling avenue for future research. Moreover, extending the validation and diverse generalization of these models to geographical regions and temporal frames could substantially bolster their utility and relevance for broader applications in rental price forecasting.All paragraphs must be indented.

V.CONCLUSIONS

The investigation into the efficacy of machine learning models for predicting room rental prices has yielded substantive insights into the factors that drive the rental market. Through meticulous evaluation using metrics such as accuracy, mean squared error, and AUC-ROC, we have established the Random Forest algorithm as a particularly effective model due to its precision and lower error rates. Simultaneously, Gradient Boosting and SVMs demonstrated a remarkable ability to process complex data and categorize rental prices effectively, with Neural Networks showcasing their deep learning advantages, albeit at a higher computational cost.

The elucidation of key features influencing rental prices through SHAP value analysis has provided a clearer understanding of market drivers. Size,

location, room count, age, and amenities proximity were confirmed as significant factors impacting rental valuation, with spatial trends and amenity proximity emerging as primary influences on pricing.

REFERENCES

- Ahuja, A., Cheung, L., Han, G., Porter, N. and Zhang, W. (2010). "Are [1] house prices rising too fast in China?" IMF Working Paper WP/10/274. Retrieved from http://www.imf.org/external/pubs/ft/wp/2010/wp10274.pdf
- [2] Eftimoski, M., & McLoughlin, K. (2019). "Housing policy and economic growth in China and Australia." Australia: Reserve Bank of Australia.
- [3] Yang, X. (2014). "The Experience of Housing Welfare Policy in Developed Countries and Its Enlightenment on China -Based on the Perspective of Structural Reform at Supplyside." West Forum, 27, 107-115.
- [4] Yuan, W. (2020). "Analysis on the current situation of the long-term rental housing market expedited by China's policy dividend and Discussion on the establishment of double custody mechanism.' Contemporary Economics, 7-9.
- [5] Ho, C., & Hensher, D. (2014). "Housing Prices and Price Endogeneity in Tenure and Dwelling Type Choice Models." Case Studies on Transport Policy, 107-115.
- [6] Anjuke. (2019, March 15). "Investigation report on rental consumption behavior." Retrieved from https://www.donews.com/news/detail/4/3039153.html.
- [7] Preston, V., & Taylor, S. M. (1981). "Personal Construct Theory and Residential Choice." Annals of the Association of American Geographers, 437-451.
- [8] Yang, L., Chau, K. W., & Chen, Y. (2021). "Impacts of information asymmetry and policy shock on rental and vacancy dynamics in retail property markets." Habitat International. Hendershott, P. H. (1996). "Bubbles in Metropolitan Housing
- [9] Markets." [Journal Name], 191 207.
- [10] Wu, Z. (2020). "Prediction of California House Price Based on Multiple Linear Regression." Academic Journal of Engineering and Technology Science, 11-15.