# Reducing property valuation bias through Random Forests: Predicting prices for public asset optimization

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ABSTRACT

This study applies supervised machine learning, specifically the Random Forest regression algorithm, to predict office rental prices in DKI Jakarta. A dataset was compiled via web scraping of online property listings, incorporating features such as location, office area, number of floors, lifts, parking capacity, and building grade. Data preprocessing involved handling missing values, removing outliers, applying one-hot encoding, and normalizing the data to ensure consistency. The model was developed using the CRISP-DM framework and evaluated through an 80:20 train-test split and 10-fold cross-validation. Performance metrics included Root Mean Squared Error (RMSE) and $R^2$. The Random Forest model achieved high accuracy, with cross-validation yielding an $R^2$ of 0.934 and an RMSE of Rp16.288 per m²/month. SHAP analysis revealed that lifts, floors, parking, office area, and building grade significantly influenced predictions. Bias analysis indicated a tendency to underestimate rents for grade B and C buildings. The model was also simulated to estimate rental values of underutilized government-owned offices, supporting asset optimization amid the planned capital relocation. These results demonstrate the potential of machine learning to improve valuation practices, reduce bias, and enhance decision-making in public asset management.



## 1. Introduction

Determining office rental prices is crucial to the property sector, as it directly influences investment decisions, tenant strategies, and government policies related to asset management. In Jakarta, Indonesia's central economic hub, the office market has faced persistent challenges due to oversupply and an imbalanced demand. Report from Colliers (2024) indicates that occupancy in the Central Business District (CBD) remains stagnant at 74.7%, while outside the CBD, it slightly improves to 77.2%. These figures indicate structural issues in the office market, where pricing uncertainty complicates decision-making for both private investors and public stakeholders. Scholars typically classify the factors influencing property value into two categories: those directly related to the physical and locational attributes of the property, and those indirectly shaped by external economic, regulatory, or social conditions. Factors that are directly related include physical aspects such as the size of the land, the building's area, and its physical condition. Meanwhile, indirect factors involve aspects of the surrounding environment, such as ease of access, environmental quality, availability of clean water, and the safety level of the area (Riyanto, 2021).

Although some factors have been identified for calculating property valuation, errors still occur in practice and have become one of the biggest challenges for the appraiser profession in recent times

(Nwosu, 2019). One of the reasons may be associated with the dominant use of conventional valuation methods, such as the market comparison and income approaches (DJKN, 2020; MAPPI, 2018), in Indonesia. Numerous studies have highlighted that these traditional techniques are prone to price bias, valuation lag, and limited transaction data (French & Gabrielli, 2004; Lorenz & Lützkendorf, 2008). Shimizu and Nishimura (2006), for instance, found significant discrepancies between government-published land prices and actual transaction values in Japan. Geltner (1997) and Bowles et al (2001) expressed similar concerns, highlighting that valuation inaccuracies have the potential to distort property indices and compromise market stability. In the Indonesian context, such weaknesses may lead to suboptimal pricing, particularly for government-owned offices that require efficient utilization of resources.

To address this issue, scholars are leveraging global advances of artificial intelligence (AI) tools and machine learning (ML) to calculate property valuation (Antipov & Pokryshevskaya, 2012; Mohd et al., 2022). However, this momentum has yet to gain significant attention in Indonesia, where empirical studies remain limited. Most Indonesian-context research has yet to explore predictive bias across building grades or examine how AI-based valuation models can be directly applied to support the optimization of state-owned assets. This gap highlights the need for an evidence-based, data-driven approach tailored to the Indonesian office rental market, particularly in light of the impending relocation of the national capital, which may result in significant office assets remaining idle. In fact, AI-based valuation models can be applied to support the optimization of state-owned assets.

This study contributes to filling that gap by developing and validating a Random Forest Regression model to predict office rental prices in Jakarta. The contribution is twofold. First, it offers a methodological advancement by applying a machine learning approach capable of reducing valuation bias compared to conventional models. Second, it provides policymakers with practical insights by simulating the use of this model to estimate competitive rental prices for underutilized state-owned properties, thereby supporting more effective strategies for optimizing non-tax state revenue (PNBP). In doing so, the research advances both academic understanding of valuation accuracy and the practical management of public assets in Indonesia.

## 2. Literature Review

Property valuation studies have widely adopted both traditional econometric models and more recent data-driven approaches. Conventional valuation methods typically rely on the Sales Comparison Approach, Cost Approach, and Income Approach, which have been the standard practice in both academic and professional contexts (RICS, 2015; MAPPI, 2018). These methods, however, often face challenges of data availability, subjectivity, and valuation bias, particularly in heterogeneous urban office markets (Crosby et al., 2006; Adams & Tolson, 2019). To address this issue, some studies have analyzed the valuation using hedonic pricing models and regression-based techniques to capture the relationship between property attributes and rental values. For example, studies in Jakarta (Mulyadi et al., 2015; Restiatun, 2021) and other Asian metropolitan cities (Le et al., 2018) have applied this hedonic model. Generally, they demonstrate that physical attributes (size, grade, amenities) and locational characteristics significantly affect office rental prices. While robust in capturing linear relationships, these models may fail to explain non-linear and interaction effects inherent in complex property markets.

The evolution of machine learning methods, including Random Forest, XGBoost, and Artificial Neural Networks, has provided more powerful tools to handle large datasets and non-linear dynamics. Prior research Čeh et al., (2018) Levantesi & Piscopo (2020) and Mohd et al (2022) has exemplified the effectiveness of Random Forest in predicting real estate prices with higher accuracy compared to multiple regression. Similarly, Ja'afar et al (2021) conducted a systematic review and concluded that ensemble methods consistently outperform traditional econometric models in predicting property prices. This study builds upon the above methodological developments by combining web scraping as a data acquisition technique with Random Forest Regression as the predictive engine. Web scraping enables the collection of real-time and large-scale office market data in Jakarta, overcoming the limitations of official datasets. Meanwhile, Random Forest, as an ensemble learning method, allows the model to reduce variance, minimize bias, and improve prediction stability. To ensure robustness, the research applied two validation techniques: (i) a split dataset approach (80:20) and (ii) 10-fold cross-validation, enabling performance comparison and accuracy benchmarking. Thus, the methodology employed in this paper represents a hybrid approach, integrating big-data collection techniques with advanced predictive analytics. This approach is positioned as a methodological enhancement to traditional property valuation practices.

## 3. Method

This study employed the CRISP-DM (Cross-Industry Standard Process for Data Mining) approach as a methodological framework for developing a predictive model of office space rental prices. The approach consists of six iterative stages: business understanding, data understanding, data preparation, modeling, evaluation, and deployment (Figure 1). In the business understanding stage, we identified the need for a model capable of accurately predicting rental prices to support decision-making for office space utilization, including state-owned assets (BMN). In line with this need, office space rental price data for Jakarta was obtained through web scraping techniques from various online property rental sites, including sewakantorcbd.com, sewakantor-online.com, and property.jll.co.id. This dataset was then enriched by secondary data gathered from property market reports published by Colliers (2024) and Knight Frank (2024), as well as land price information derived from the Selling Value of Tax Objects (NJOP).

The collected data included variables that significantly influenced the office space rental prices, such as the rental price per square meter, building grade, room area, number of floors, number of elevators, number of parking spaces, building location, and land prices based on the NJOP. In the data understanding stage, an exploration of building specification data, such as the number of floors, space area, elevator parking capacity, and building grade, was conducted to understand the distribution and quality of the data. Meanwhile, the data preparation stage involved processes such as data cleaning, handling missing values, normalization, and transforming categorical variables to prepare the data for modeling. To ensure the integrity and cleanliness of the datasets, a cleaning process was performed to remove duplicate entries, address missing values, and identify and eliminate outliers that could compromise the accuracy of model predictions. Additionally, data transformation was performed to optimize the usability of all variables within the dataset for machine learning modeling. Categorical variables, such as building grade and location, were converted using one-hot encoding. In contrast, numerical variables, such as room area and number of floors, were normalized to have a uniform scale.

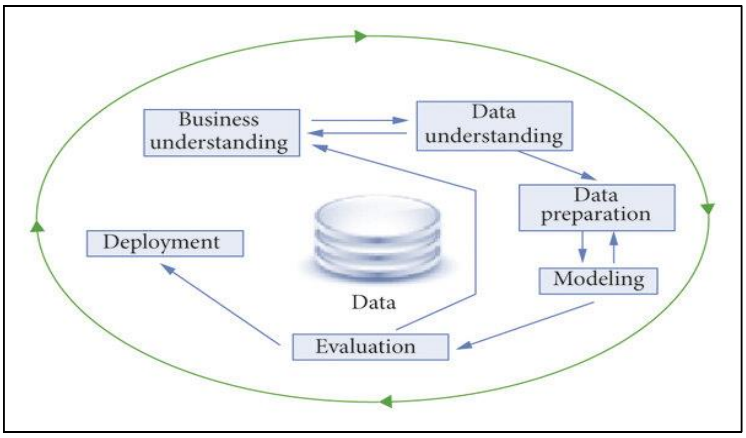


**Figure 1**. The cross-industry standard process for data mining (CRISP-DM)

During the modeling stage, this study developed a predictive model using the Random Forest Regression algorithm, selected for its robustness in handling complex datasets, its ability to capture non-linear relationships among variables, and its mitigation of the risk of overfitting through ensemble learning techniques. The model was then optimized using a grid search to determine the best parameter values, including the number of decision trees (n_estimators), the maximum depth of the tree (max_depth), and the number of features used at each decision tree (max_features).

The model’s effectiveness was evaluated using two validation approaches: the split method (80:20) and 10-Fold Cross-Validation. In the split method, the data was divided into 80% for training and 20% for testing. In contrast, the cross-validation approach employed K-Fold Cross-Validation (K=10) to ensure that each data point alternated between the training and test datasets to enhance the model’s stability and generalizability (James et al., 2013). The Random Forest Regression method, which was evaluated using 10-Fold Cross-Validation, had the best performance in predicting house prices with a Root Mean Squared Error (RMSE) of 0.440, lower than the Linear Regression and Gradient Boosted

Trees Regression methods, thus proving that cross-validation is more effective in reducing the risk of overfitting and improving the reliability of the prediction model (Fitri, 2023).

After that, the evaluation stage was conducted to assess the extent to which the model met the analytical objectives, including identifying potential prediction bias between property classes. The model was evaluated using two primary metrics. R-Squared ($R^2$) was used to explain variations in rental prices, where a value close to 1 indicates a high degree of accuracy. In addition, the Root Mean Square Error (RMSE) was used to measure the average prediction error generated by the model. The smaller the RMSE value, the better the model in predicting the rental price of office space.

In addition to evaluating the model's accuracy, the study also focused on bias analysis in rental price prediction models. This stage included a comparative error analysis to compare the predicted results with actual transaction prices and identify whether the model tends to underestimate or overestimate rental prices in specific categories. After that, a feature analysis was conducted using the SHAP (Shapley Additive Explanations) method to identify the primary factors most influential in determining the rental price of office space. Finally, a residual analysis was used to examine the distribution of prediction errors to determine whether there are specific patterns of bias in a particular property category or location.

After obtaining the optimal model, this study simulated its application during the deployment stage. In particular, a simulation of the model's application was conducted to optimize BMN (State Property) assets that may become idle assets following the relocation of the State Capital (IKN) to East Kalimantan. This simulation estimated the optimal rental price for BMN assets based on current market conditions and determined pricing strategies to increase PNBP (Non-Tax State Revenue) from state assets no longer used by government agencies. Thus, the developed model not only contributes to more accurate property valuation methods but also provides practical recommendations for managing state assets to make them more efficient and profitable.

All data and analyses in the study were conducted using Python, with the Scikit-Learn, Pandas, NumPy, and SHAP libraries employed for data analysis and machine learning modeling. Programming was done through Jupyter Notebook, while data visualization and residual analysis were done using Matplotlib & Seaborn. Data storage and management were handled using PostgreSQL and SQLite to ensure data integrity and efficiency in the processing of large amounts of data. With the approach described, this study produces a more accurate model for predicting office space rental prices and provides deeper insight into the main factors that affect rental prices in Jakarta. In addition, the bias analysis provides a broader understanding of the extent to which machine learning models can be used in property valuations and how these models can be optimized to reduce bias in property price predictions.

## 4. Results and Discussion

This study developed a predictive model for office space rental prices using Random Forest Regression. The model was evaluated using two validation approaches: split and cross-validation. The results showed that the cross-validation approach with K=10 achieved higher accuracy than the split approach. Table 1 shows that the model yielded an $R^2$ of 0.163 and an RMSE of Rp 49.148. This finding indicates that the model still has a relatively high error rate in predicting the office rental price. Meanwhile, with the cross-validation approach, the $R^2$ value increased to 0.934, while the RMSE decreased to Rp 16.288. These differences reflect a 66.9% reduction in prediction error, underscoring the robustness of cross-validation in capturing non-linear relationships and ensuring model stability across diverse data segments. On the other hand, the split approach is less optimal for capturing patterns in the dataset. One possible reason is that it uses only one data split, making it vulnerable to bias from uneven data distributions between the training and test data, Consequently, model performance becomes sensitive to the choice of data partition rather than reflecting the true data structure. In contrast, the cross-validation approach provides more stable results because each part of the dataset is used alternately (in turn) as training and test data.

**Table 1.** Comparison of Model Accuracy Based on Validation Method

| Validation Method | $R^2$ | RMSE (Rp/m$^2$/month) |
|---|---|---|
| Split Approach (80:20) | 0.163 | 49.148 |
| Cross-Validation (K=10) | 0.934 | 16.288 |

Source: data processed

Following that, this study analyzed factors that affected the rental price of office space in Jakarta. To do so, it employed the SHAP (Shapley Additive exPlanations) method, which identifies the variables with the most significant contributions to the prediction model. The results showed several variables that mostly influence rental prices, such as the number of elevators, floors, parking spaces, the area of office space, and the building's grade.

**Table 2.** Factors Affecting Rental Prices Based on SHAP Value

| Variable | SHAP Value | Interpretation |
|---|---|---|
| Number of Elevators | 0.203 | The more elevators a building has, the higher the rental price |
| Number of Floors | 0.183 | High-rise buildings tend to have higher rental prices |
| Number of Parking | 0.138 | The large parking capacity enhances the building's value |
| Room Size | 0.130 | Larger office space has higher rental prices |
| Building Grade | 0.104 | Grade A buildings are more expensive than Grade B and C buildings |

Source: data processed

As shown in Table 2, the number of elevators had the most significant influence on rental prices. Buildings with more elevators tend to have higher rental prices, possibly because elevators enhance comfort and mobility efficiency, especially in high-rise buildings. Additionally, the number of floors in a building significantly contributes to rental prices, as high-rise buildings typically offer more comprehensive facilities, better accessibility, and greater appeal to large companies that require premium office space. Furthermore, the number of parking spaces in the building is another factor that affects the rental price of office space. A large parking capacity tends to increase rental prices, especially for tenants who need parking access for their employees and clients. In addition, the size of office space contributes to determining rental prices. It is noted that office space with a larger area is generally more expensive, especially if it is located in a business center with high demand. Another significant factor is the building grade. Grade A buildings have higher rental prices than grade B and grade C buildings because they offer premium facilities, strategic locations, and a higher level of security. The categorization of these buildings is based on Colliers (2024) frameworks. A bias analysis was applied to identify biases in the prediction of office space rental prices by comparing prediction errors across building grade and location. The results of the bias analysis in the model are presented in Table 3.

**Table 3**. Comparison of Prediction Errors

| Grade of Building | Average Prediction Error (%) | Interpretation |
|---|---|---|
| Grade A | 4.5% | High accuracy, slight bias |
| Grade B | 9.2% | Tends to have a bias |
| Grade C | 12.8% | Tends to have a bias |

Source: data processed

Table 3 shows that the model tended to predict rental prices more accurately for buildings with grade A. Meanwhile, the model tended to underestimate the rental price of buildings with grades B and C. This bias can occur because the datasets used for model training are more inclusive of higher-priced buildings Jakarta's business center, making it less likely to capture rental price patterns in suburban areas or in buildings with limited facilities. Figure 2 shows the scatter diagram of predicted versus actual values, illustrating how the model performs across building grades. Most grade A points cluster closely around the 45° line, indicating accurate predictions. In contrast, grade B and grade C properties tend to fall below the line, which means systematic underestimation by the model.

Table 4 shows that the model accuracy varies substantially across building classes. For grade A offices, the mean prediction error was negligible (−0.03%), indicating highly reliable estimates with an MAE of only Rp9,718/m². In contrast, grade B offices showed a moderate overestimation of 6.78%, while grade C offices experienced the highest bias, with a mean overestimation of 17.08% and an MAE of Rp21,311/m² /m². These results suggest that the model performs best for premium assets but tends to overvalue lower-grade offices. Thus, additional explanatory variables are needed to improve model calibration for grades B and C. The model should be refined with additional macroeconomic or location-related attributes to reduce grade-related bias.

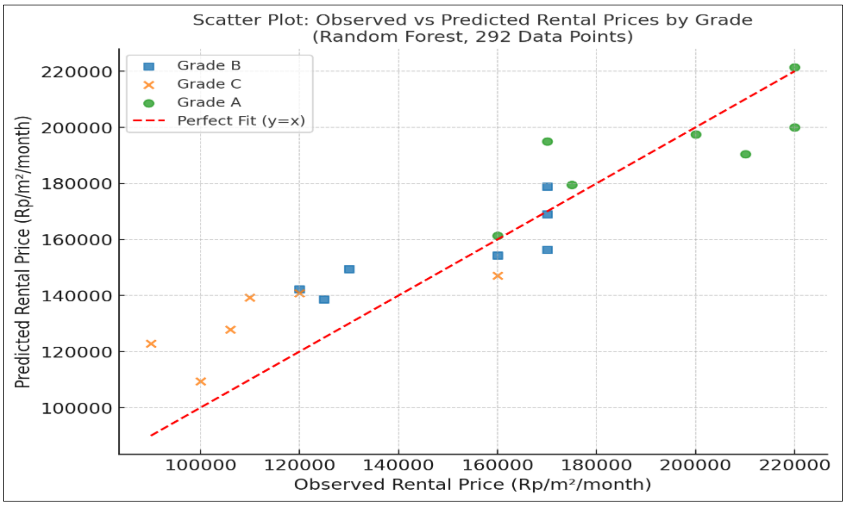


**Figure 2**. Scatter Diagram of Rental Prices by Grade

After obtaining the optimal rental price prediction model, this study also simulates its application to optimize BMN (State-Owned Goods) assets that may become idle, especially after the relocation of the State Capital (IKN) to East Kalimantan. The simulation results demonstrate that the developed model can be utilized to estimate competitive rental prices for BMN assets, enabling the government to devise a more effective asset utilization strategy and increase PNBP (Non-Tax State Revenue). By using more accurate rental price predictions, BMN assets located in strategic locations with complete facilities can be rented at more competitive rates, thereby increasing the country's revenue potential.

**Table 4**. Bias Analysis per Building Grade

| Grade | Mean Actual (Rp/m$^2$/month) | Mean Predicted (Rp/m$^2$/month) | Mean Error (Rp) | Mean % of Error | MAE (Rp) |
|---|---|---|---|---|---|
| A | 185.714 | 183.134 | -2.580 | -0.03% | 9.718 |
| B | 152.500 | 161.633 | 9.133 | 6.78% | 13.949 |
| C | 113.200 | 129.370 | 16.170 | 17.08% | 21.311 |

Source: data processed

This study contributes to the development of a more accurate, data-driven, and applicable property valuation method that supports property asset management policies in Indonesia. The developed model can serve as a reference for determining a more market-based rental price strategy, as well as for managing property assets to maintain productivity and high economic value. From a policy perspective, these results provide direct implications for state asset management. First, the model can serve as a benchmarking tool for the government in setting competitive rents for idle state-owned offices. Second, it allows PNBP simulation. For example, 10,000 m² of idle grade B office space, predicted to be worth Rp 200,000/m², would generate Rp 2 billion annually. If underestimation bias (−9.2% or Rp25,000/m² /month) persists, the potential revenue loss could reach Rp3 billion per year for the same space. Third, the model can be integrated into asset management systems such as SIMAN. Such integration aligns with Ministry of Finance regulations (e.g., PMK 115/2020) to ensure faster, data-driven decisions.

## 5. Conclusion

This study demonstrates that applying machine learning, particularly Random Forest Regression, to predicting office space rental prices in Jakarta yields more accurate results than traditional methods. Evaluated using two validation approaches (split and cross-validation), this study showed that the cross-validation method with K=10 performed better, with an $R^2$ of 0.934 and an RMSE of Rp 16.288, compared to the split approach, which only produced an $R^2$ of 0.163 and an RMSE of Rp 49.148. This study also identifies the main factors contributing to office rental prices, such as the number of elevators, floors, parking spaces, the area of the office space, and the building's grade. Buildings with more comprehensive facilities and higher quality tend to command higher rents. Finally, the analysis of bias revealed that the model tends to be more accurate at predicting rental prices for grade A buildings. In contrast, grade B and C buildings are often underestimated, suggesting that the model still needs improvement by considering macroeconomic factors such as market conditions, occupancy rates, and government policies.

This study simulates the application of the model to optimize BMN (State-Owned Goods) assets that may become idle after the relocation of the State Capital (IKN). The developed rental price prediction model can be used to determine a more competitive rental price for BMN assets, and to inform the strategy to increase PNBP (Non-Tax State Revenue). As such, this model is not only valuable for academic analysis but also has real potential applications in the management of state assets and the commercial property sector. The implication of the study is the development of a more accurate, transparent, and data-based property valuation method. By utilizing this technology, policymakers and property industry players can enhance the accuracy of rental price estimates, minimize valuation bias, and optimize property asset utilization strategies, both in the private sector and for government-owned assets. Still, further research can be conducted by incorporating macroeconomic variables and other external factors to enhance the prediction accuracy and broaden the model's application to other property sectors.

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| | | |
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## References

Adams, D., & Tolson, S. (2019). Valuation in the dark: Constructing perception of normality in failing markets. *Town Planning Review, 90*(4), 383–406. doi: 10.3828/tpr.2019.23

Antipov, E. A., & Pokryshevskaya, E. B. (2012). Mass appraisal of residential apartments: An application of random forest for valuation and a CART-based approach for model interpretation. *Expert Systems with Applications, 39*(2), 1772–1778. doi: 10.1016/j.eswa.2011.08.077

Bowles, G., McAllister, P., & Tarbert, H. (2001). An assessment of the impact of valuation error on property investment performance measurement. *Journal of Property Investment & Finance, 19*(2), 139–155. doi: 10.1108/14635780110383695

Čeh, M., Kilibarda, M., Lisec, A., & Bajat, B. (2018). Estimating the performance of Random Forest versus multiple regression for predicting prices of apartments. *ISPRS International Journal of Geo-Information, 7*(5), 168-180. doi: 10.3390/ijgi7050168

Colliers International. (2024). *Jakarta office market report Q1 2024*. Colliers International.

Crosby, N., Hughes, C., & Murdoch, S. (2006). Exit strategies for business tenants. *Journal of Property Research, 23*(3), 215–236. doi: 10.1080/09599910600933848

DJKN. (2020). *Guidelines for the valuation of state property*. Ministry of Finance of the Republic of

Indonesia.

Fitri, E. (2023). Comparative analysis of linear regression methods, random forest regression, and gradient boosted trees regression for predicting home prices. *Journal of Applied Computer Science and Technology, 4*(1), 58–64. doi: 10.52158/jacost.v4i1.491

French, N., & Gabrielli, L. (2004). The uncertainty of valuation. *Journal of Property Investment & Finance, 22*(4), 329–346. doi: 10.1108/14635780410569470

Geltner, D. (1997). The use of appraisal in portfolio valuation and index construction. *Journal of Property Investment & Finance, 15*(5), 423–447. doi: 10.1108/14635789710189191

Ja'afar, N. S., Mohamad, J., & Ismail, S. (2021). Machine learning for property price prediction and price valuation: A systematic literature review. *Planning Malaysia, 19*(4), 56–70. doi: 10.21837/pm.v19i17.1018

James, G., Witten, D., Hastie, T., & Tibshirani, R. (2013). *An introduction to statistical learning: With applications in R*. Springer. doi: 10.1007/978-1-4614-7138-7

Knight Frank. (2024). Greater Jakarta property market outlook. Knight Frank.

Le, V. T., Nguyen, H. Q., & Nguyen, V. T. (2018). Analysis of factors affecting Ho Chi Minh city's office rental prices using a hedonic model. *MATEC Web of Conferences, 193*, 05041. doi: 10.1051/matecconf/201819305041

Levantesi, S., & Piscopo, G. (2020). The importance of economic variables on the London real estate market: A Random Forest approach. *Risks, 8*(4), 112-124. doi: 10.3390/risks8040112

Lorenz, D., & Lützkendorf, T. (2008). Sustainability in property valuation: Theory and practice. *Journal of Property Investment & Finance, 26*(6), 482–521. doi: 10.1108/14635780810908361

MAPPI. (2018). *Kode Etik Penilai Indonesia dan Standar Penilaian Indonesia (KEPI & SPI) Edisi VII-2018*. Masyarakat Profesi Penilai Indonesia.

Mohd, T., Harussani, M., & Masrom, S. (2022). Rapid modelling of machine learning in predicting office rental price. *International Journal of Advanced Computer Science and Applications, 13*(12), 567–573. doi: 10.14569/IJACSA.2022.0131271

Mulyadi, E., Miyasto, H., & Sugiyanto, F. X. (2015). Model nilai sewa ruang perkantoran pada kawasan pusat bisnis di Jakarta. *Jurnal Ekonomi dan Bisnis Indonesia, 30*(3), 245–258.

Nwosu, A. E. (2019). Valuation inaccuracy: Implications on commercial property investment performance in Akure. *Nigeria. Journal of African Real Estate Research, 4*(1), 92–107. doi: 10.15641/jarer.v0i0.712

Restiatun. (2021). Determinants of the office space rent rate in Jakarta, Indonesia. *Indian Journal of Economics and Business, 20*(3), 765–776.

RICS. (2015). *Our changing world: Let us be ready*. Royal Institution of Chartered Surveyors. Washington DC.

Riyanto, E. (2021). Identification of factors that affect residential property value based on the perception of government appraisers. *Info Artha, 5*(1), 55–65. doi: 10.31092/jia.v5i1.1176

Shimizu, C., & Nishimura, K. G. (2006). Biases in Appraisal Land Price Information: The Case of Japan. *Journal of Property Investment & Finance, 24*(2), 150–175. doi: 10.1108/14635780610655085