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Office Rent Prediction based on the Influenced Features

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Abstract
This study applies a new approach in identifying the best Machine Learning model to predict office rent and determining the most significant factors influencing rental values. The Auto Model uses three (3) distinct types of Machine Learning algorithms, namely the Decision Tree, Random Forest, and Support Vector Machine. The Auto Model highlights that the Decision Tree outperformed Random Forest and Support Vector Machine for better prediction. The results of statistical analysis using Auto Model suggest that among the factors that influence office building rental, amenities, and in-house services show significant roles in the model.

Keywords: Office Rent, Machine Learning, Prediction

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1.0 Introduction

In finding a reliable and consistent model in predicting the rental of office buildings, numerous models have been proposed previously, for instance, the econometric model, discounted cash flow, and system dynamics. Still, limited success was achieved in finding a reliable and consistent model to predict rental property market movements over a five-to-ten-year time frame (Tonelli et al., 2018). Due to the vulnerability to macro-effects and performance of real estate within the market where office buildings are more synchronous than others, the heterogeneity of office space features somehow makes them more complex to analyse (Gjerland et al., 2019). This poses a gap as accurate predictions of real estate rentals are critical for investors and other real estate market stakeholders. With the spreading spectrum of Industrial Revolution 4.0, a specific computing approach known as Machine Learning, optimised for property market analysis, is undoubtedly the most acceptable solution (Dimopoulos & Bakas, 2019). Various studies confirm that Machine Learning Model is associated with research related to predicting and classifying real estate prices where this model can solve the inherent problems (Čeh et al., 2012; Dimopoulos & Bakas, 2019; Modi et al., 2020; Zhou et al., 2019). Hence, this study will fill the gaps by implementing a robust approach by

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identifying the best Machine Learning model in predicting office rent based on the influencing factors and determining the most significant factor influencing office building rental based on Machine Learning Auto Modelling.

2.0 Literature Review

2.1 Office Building Rent Determinants

Rent is vital in property assessment since every positive or negative influence on rent will affect the value of a property. Key property market participants such as investors and developers, frequently use rental values to assess their real estate development and investment projects (Ojok, 2018). The International Valuation Standard (IVS) defines market rent as "the estimated amount for which an interest in real property should be leased on the valuation date between a willing lessor and a willing lessee on appropriate lease terms in an arm's length transaction, after proper marketing, and where both parties acted knowledgeably, prudently, and without compulsion". Over the past few years, various research has been implemented to study office rent determinants. For instance, Bera (2019) signifies that a building's physical appearance, amenities and in-house services, neighbourhood, and market operational characteristics have global and local effects on office rent. Wei (2003) highlights macroeconomics determinants such as GDP, lending rates, and employment rates. The study primarily focused on Southeast Asian cities like Kuala Lumpur, Bangkok and Singapore. The findings, however, show that macroeconomic determinants do not significantly affect these regions. Another example can be discovered in Hui (2015), where the researcher indicates that locational trade-off theories address price and rental variations. A building within the CBD is likewise strongly positively connected with office rentals in the sample of commercial buildings (Safian & Nawawi, 2013). Another example can be seen in Fuh Yiing (2013), where the authors highlight that green certificate factors can influence office rents. Hence, due to the significant uncertainties and dynamic variables in analysing office rent, this study will highlight specific determinants through Machine Learning model development.

2.2 Machine Learning in Real Estate

Real estate is no longer a specific industry that depends on professional valuation judgments. Due to existing connections with various factors, the real estate market is subject to significant price changes, some of which cannot be controlled or are even unknown. Machine Learning has been adapted in various research areas over the last decade, and its versatility has attracted the use of algorithms for multiple applications. Recent studies have demonstrated that Machine Learning models effectively predict, estimate, and forecast real estate sales, prices, and rentals. These include property selling prices (Baldominos et al., 2018), property rental prices (Zhou et al., 2019), and agricultural land values (Er, 2018). The accuracy of the Machine Learning Model's output is dependent on several factors including the researcher's selection, configuration, parameters, and techniques. A previous study by Phan (2018) stated that Machine Learning in the real estate market could be divided into trends in forecasting the house price index and house price valuations. The author uses a vector auto-regression model to predict the house price index. In conducting house price valuations, the author employs support vector machines.

3.0 Research Method

3.1 Data Collection

Kuala Lumpur city centre was chosen as the research area. The significance of selecting the Kuala Lumpur city centre was due to the high concentration of office buildings (Adnan et al., 2012). The Kuala Lumpur city centre, which includes Seksyen 1-100, is a large region that spans numerous main streets and is renowned as Kuala Lumpur's business, shopping, and entertainment hub. It is Kuala Lumpur's business, retail, and entertainment district, and it encompasses a large area with multiple major routes. The physical manifestation of its physical function as a business and office location activity is seen in the emergence of the Golden Triangle area (the area bounded by Jalan Ampang, Jalan Sultan Ismail, and Jalan Bukit Bintang), which is surrounded by international hotels and office and commercial blocks (Adnan & Daud, 2010). The related data were acquired from the Valuation and Property Services department (JPPH), comprising 722 office space transactions covering 191 office buildings in the Kuala Lumpur city centre area. The acquired data ranging from the year 2015-to 2021 was employed for analysis. After the cleaning process, the 693 transactions with 18 columns were included for the Machine Learning Auto Model. The methodology uses data analytic tools, namely the RapidMiner Studios, to evaluate which factors substantially impact office rents using correlation weights based on Auto Model analysis. Table 1 indicates the selected variables on factors affecting office building rents.

Table 1. Selected Variables on factors affecting office building rents

Variables
MSc Status
Green Certificate
Building Appearance and Design
Building Age
Amenities and In-House Services
Finance, Insurance and Real Estate Average
Vacancy Rate
Inflation
GDP

Distance to City Centre
Neighbourhood Characteristics
Traffic Condition
Nearest Public Transport
Tenancy Duration
Service Charge
Transaction Date
Rentable Area
Employment Rate

(Source: Researcher, 2021)

3.2 Algorithms Selection

During this process, the Auto Model will automatically generate the best Machine Learning algorithms based on the nature of the loaded datasets. Based on the results of the Auto Model, three (3) algorithms were suggested, namely 1) Decision Tree, 2) Random Forest, and 3) Support Vector Machine. It was proven from previous studies that these algorithms were widely used to predict real estate market performances. For instance, Čeh (2018) implemented a Random Forest Machine Learning technique for the prediction of apartment prices, rent prediction for housing purposes via a Decision Tree (Zhou et al., 2019), and Support Vector Machine to study the house price prediction (Baldominos et al., 2018).

3.3 Machine Learning Configurations

Optimal Parameter is a strategy for making the Machine Learning Auto Model a good prediction model by modifying its parameters. It uses an optimisation search to determine the optimum Machine Learning settings, which rely on the dataset's structure. Table 2 indicates the optimal parameter for the Decision Tree algorithm.

Table 2. Decision Tree Optimal Parameter

Maximal Depth	Error Rate
2	63%
4	35.7%
7	21.1%
10	20.5%
15	**20.1%**
25	20.1%

(Source: Researcher, 2021)

Based on the analysis, the relevant parameter is maximal depth. As listed in Table 2, six (6) values of maximal depth have been observed. It has been identified that the lower error rate was generated with 15 maximal depths. Thus, the best optimal parameters to be distinguished on the Decision Tree for this study is at *maximal depth = 15* with a *20.1% error rate*. Table 3 shows the optimal parameter for the Random Forest algorithm.

Table 3. Random Forest Optimal Parameter

Number of Trees	Maximal Depth	Error Rate
20	2	65.8%
60	2	65.3%
100	2	65.6%
140	2	65.2%
20	4	52.1%
60	4	54.2%
100	4	54.5%
140	4	54.2%
20	7	47.2%
60	7	44.5%
100	**7**	**44.2%**
140	7	47.0%

(Source: Researcher, 2021)

Random Forest extends the Decision Tree algorithm, which has one additional parameter besides the maximal depth. As shown in Table 3, the maximal depth is dedicated to the internal sub-trees. Based on 12 configurations of sub-trees and depths, the most optimal setting is presented by 100 trees and 7 maximal depths. This configuration generated a *44.2% error rate*.

Table 4. Support Vector Machine Optimal Parameter

Gamma (RBF)	C	Error Rate
0.005	10	59.3%
0.050	10	59.3%
0.500	10	56.4%
5	10	56.5%
0.005	100	55.7%
0.050	100	54.7%
0.500	100	56.2%

5	100	56.4%
0.005	1000	48.5%
0.050	**1000**	**43.5%**
0.500	1000	53.8%
5	1000	55.2%

(Source: Researcher, 2021)

Based on the analysis, Table 4 shows that the suggested optimal parameter for Support Vector Machine algorithms is based on Radial Basis Function (RBF) kernel and C value. The C parameter instructs the SVM optimisation to avoid misclassifying each training example. The kernel function is used to transform the data, increasing its dimensionality. This enhancement causes the data to be split with a hyperplane with a significantly greater probability, establishing a minimal prediction probability error measure (Graczyk et al., 2009). The optimal parameter configuration suggested by the Auto Model for the Support Vector Machine algorithm is at *RBF = 0.050, C = 1000, and 43.5% error rate.*

4.0 Findings

This section presents the results of the Machine Learning models in two (2) divisions. Firstly, the development of office rent prediction by Machine Learning Auto Model based on influencing factors. Secondly, the most significant factor influencing office building rental is determined based on the developed model.

4.1 Machine Learning Performances

This study employs the regression performance, which is solely utilised for regression tasks. Regression is a numerical prediction technique and a statistical measure that examines the strength of the correlation between one dependent variable and a set of other changing variables known as independent variables. The coefficient of determination (R2) and the Relative Error will be used as performance measurements to achieve the research's objectives. R-Squared is a statistical metric that indicates the proportion of the variation explained by the independent variables for the dependent variable. The greater the R-squared, the better the model matches the dataset under consideration. On the other hand, the relative error is the average value deviation of prediction from the actual value divided by the true value.

Table 5. The R^2 and Relative Error results

Machine Learning Algorithms	R^2	Relative Error
Decision Tree	0.973	19.4%
Random Forest	0.900	41.3%
Support Vector Machine	0.741	42.1%

(Source: Researcher, 2021)

Based on Table 5 is shows that the most outperformed model is the Decision Tree algorithm with 97% fitness and 19.4% relative error. Th

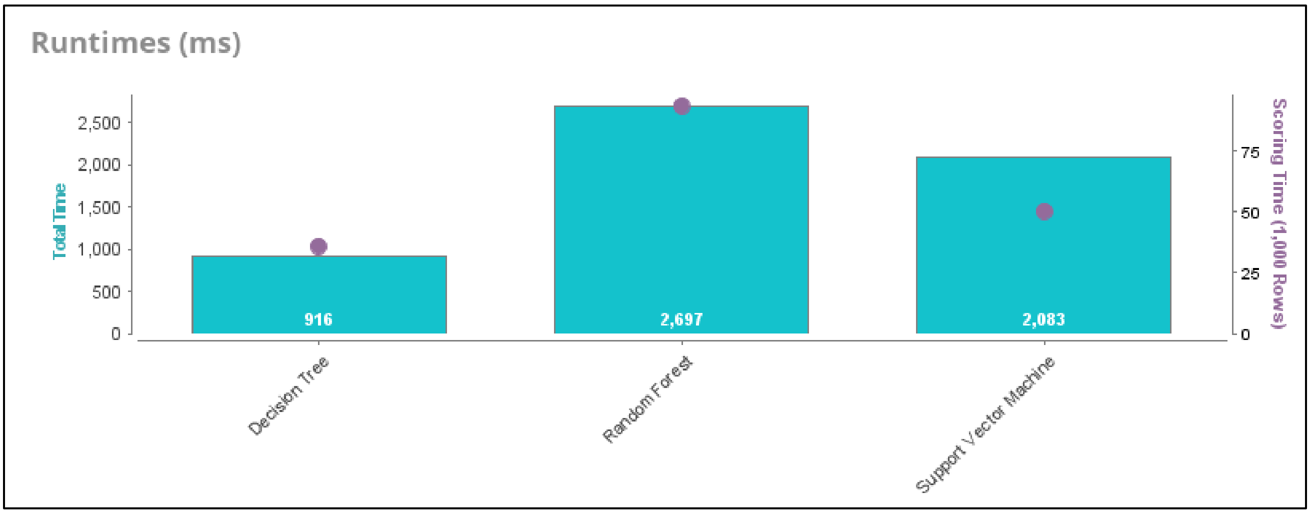

Fig 1. The efficiency of each Machine Learning model measured from the total time
(Source: Researcher, 2021)

e result generated by the Random Forest algorithm also shows a slight difference in terms of R^2 with 90% fitness. Still, there was a significantly massive difference in relative error with 41.3% as compared to the Decision Tree. The Support Vector Machine algorithm shows 74% fitness and 42.1% relative error. The R^2 result generated by the Support Vector Machine algorithm is seemingly lower than the other two (2) algorithms. Although the results generated by the mentioned algorithms are within a reasonable range, the Decision Tree algorithm produced the best R^2 and relative error as compared to Random Forest and Support Vector Machine algorithms. Additionally, in terms of efficiency in completing the prediction, the Decision Tree was the fastest algorithm as presented in Figure 1. It took only 916ms seconds of total time to complete the training and prediction testing. Meanwhile, both Random Forest and Support Vector Machine took 2697ms and 2083ms, respectively.

4.2 Office Rent Prediction

By considering the Decision Tree, Random Forest and Support Vector Machine algorithms, this study will illustrate the predicted rents versus the actual values. Based on the illustrations provided in Fig. 2, Fig. 3 and Fig. 4, the accuracy of each model will be analysed based on the predicted values (blue dot). The illustrations will be analysed by observing the blue dot; the placement of the blue dot above the red line indicates that the predicted value is higher than the true value, while the order of blue dot below the diagonal red line means that the predicted value is lower than the true value. To simplify, the closer the blue dot is to the diagonal red line (true value), the better the model predicts rent values.

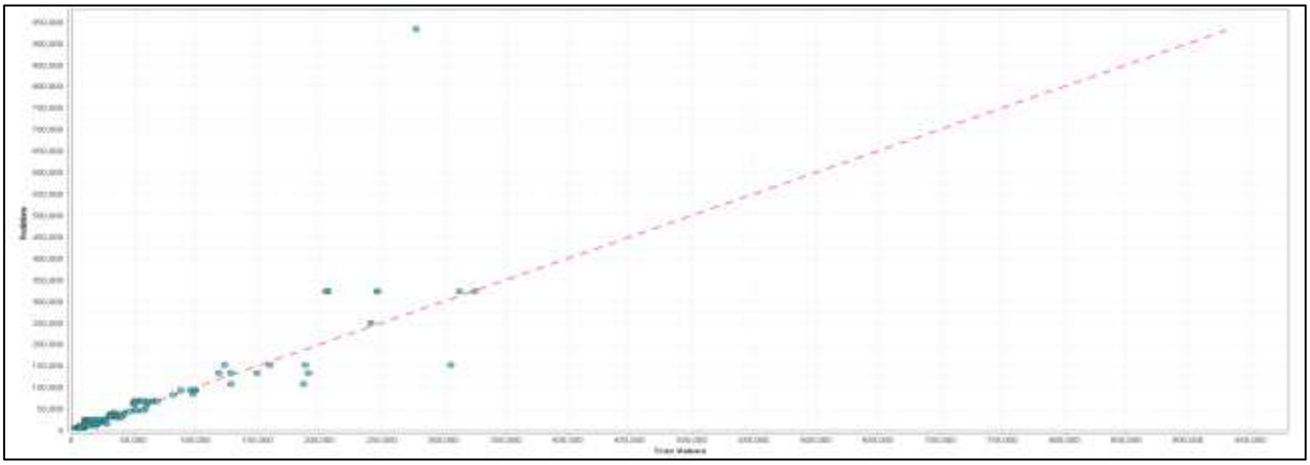

Fig 2. The prediction chart of Decision Tree
(Source: Researcher, 2021)

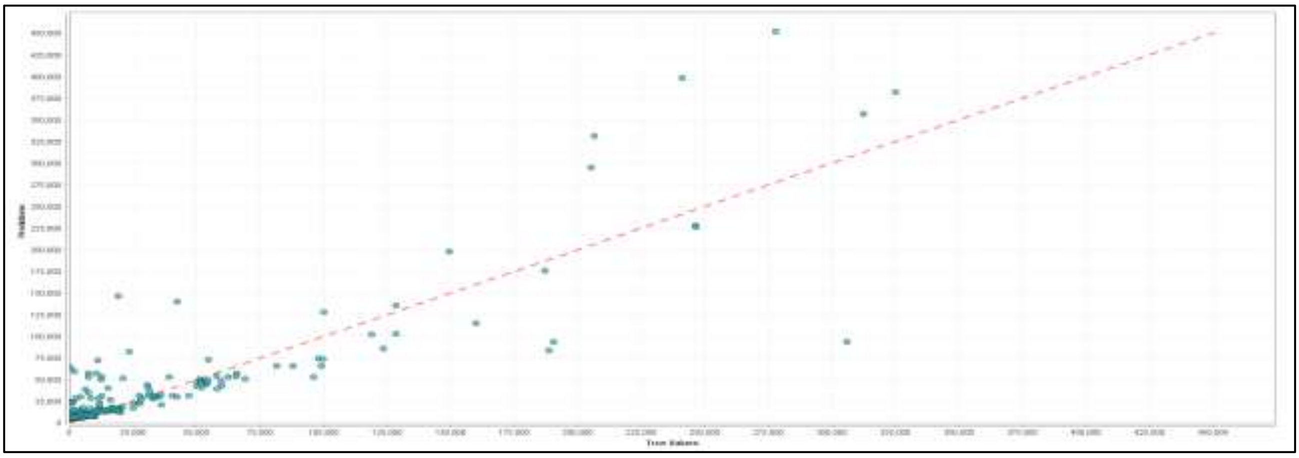

Fig 3. The prediction chart of Random Forest
(Source: Researcher, 2021)

Based on the illustrations provided in Fig. 2, Fig. 3 and Fig. 4; Fig 2 which represents the Decision Tree model, exhibits the highest concentration of blue dots to the diagonal red line. In comparison with the Random Forest model in Fig 3, the blue dots are seemingly scattered and predict a higher value since some of the blue dots were above the diagonal red line. Conversely, the Support Vector Machine model in Fig 4 is lower in accuracy since the blue dots were mainly below the red line.

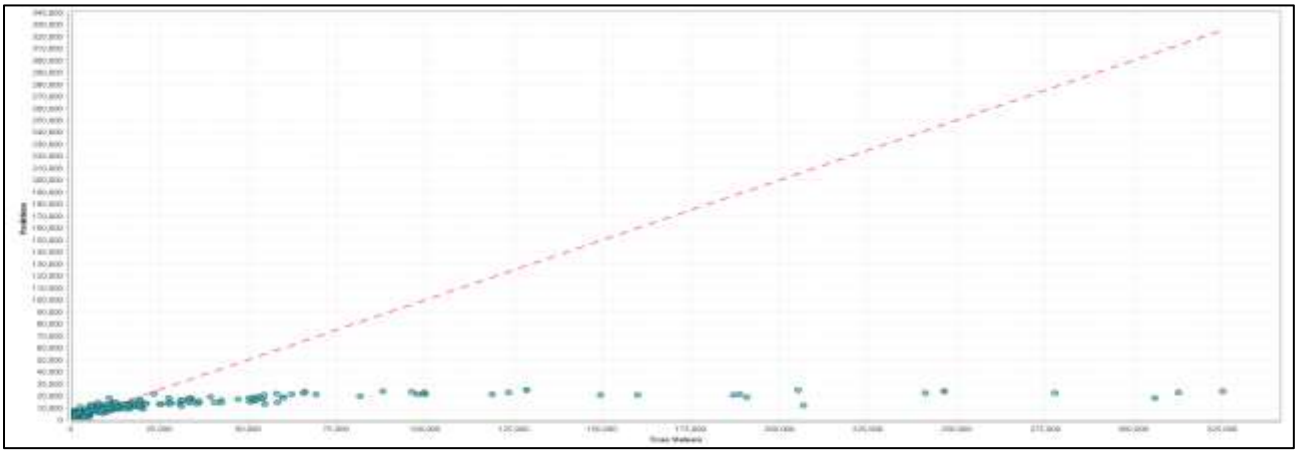

Fig 4. The prediction chart of Support Vector Machine
(Source: Researcher, 2021)

4.3 Correlation of variables in Machine Learning Auto Model

This section explains the importance of independent variables in each suggested Machine Learning model. Table 6 presents the weight of correlation of each independent variable in the Decision Tree model.

Table 6. Weight of Correlation of each Independent Variable in Decision Tree

Attributes	Weight
Amenities and In-house Services	0.785
Rentable Area	0.523
Building Appearance and Design	0.423
Nearest Public Transport	0.271
Service Charge	0.113
Building Age	0.112
Green Certificate	0.071
Average Vacancy Rate	0.069
Tenancy Duration	0.054
MSc Status	0.053
Employment Rate	0.051
Neighbourhood Characteristic	0.044
Transaction Date	0.043
Finance, Insurance and Real Estate	0.041
Inflation	0.009
GDP	0.003
Traffic Condition	0.006
Distance to City Centre	0.002

(Source: Researcher, 2021)

In Table 6, amenities and in-house services have a substantial correlation weight (0.785) with office rents in the Decision Tree model. Other independent variables included ostensibly show a weak correlation to the rent values. On the contrary, as shown in Table 7, the Random Forest generates a different result in correlation weight than the Decision Tree.

Table 7. Weight of Correlation of each Independent Variable in Random Forest

Attributes	Weight
Rentable Area	0.596
Amenities and In-house Services	0.239
Building Appearance and Design	0.191
Average Vacancy Rate	0.066
Service Charge	0.063
Building Age	0.047
Employment Rate	0.025
Neighbourhood Characteristic	0.024
Traffic Condition	0.019
MSc Status	0.011
Nearest Public Transport	0.006
Green Certificate	0.006
Distance to City Centre	0.002
Finance, Insurance and Real Estate	0.002
Inflation	0.002
Transaction Date	0.000

GDP	0.000
Tenancy Duration	0.000

(Source: Researcher, 2021)

The result generated by Random Forest, as shown in Table 7, indicates that rentable area has a strong correlation (0.596) weight with office rent. Compared to the Decision Tree, the amenities and in-house services variable is the most crucial variable; correlation weight generated by Random Forest somehow addressed that the variable only achieved a weak correlation (0.239) weight. Lastly, Table 8 shows the correlation of included independent variable in the Support Vector Machine model.

Table 8. Weight of Correlation of each Independent Variable in Support Vector Machine

Attributes	Weight
Amenities and In-house Services	0.545
Rentable Area	0.320
Building Appearance and Design	0.272
Nearest Public Transport	0.183
Service Charge	0.096
Building Age	0.071
Green Certificate	0.065
Average Vacancy Rate	0.061
Tenancy Duration	0.053
MSc Status	0.051
Employment Rate	0.051
Neighbourhood Characteristic	0.039
Transaction Date	0.036
Finance, Insurance and Real Estate	0.027
Traffic Condition	0.020
Distance to City Centre	0.009
Inflation	0.004
GDP	0.002

(Source: Researcher, 2021)

Table 8 indicates the result generated by the Support Vector Machine model. It shows that the most important independent variables are amenities and in-house services with moderate correlation at (0.545) weight, thus signifying the importance of this independent variable in developing the model. The correlation results generated in Table 6 show that the Decision Tree model also represents the same independent variable as the most influential factor in determining office rent. Hence, the comparison of each model in Machine Learning analysis shows that amenities and in-house services as the most significant variable in determining and predicting office rent values.

5.0 Discussion

This study identifies the best Machine Learning model in predicting office rent based on the influencing factors and determines the most significant factor influencing office building rental based on Machine Learning Auto Modelling. The finding discovers that by predicting office rent values using three (3) different types of models in Machine Learning, namely 1) Decision Tree, 2) Random Forest, and 3) Support Vector Machine, the Decision Tree model demonstrates the best accuracy as compared to the other models. Hence, the researcher highlights that the decision tree model is the best model to be used in predicting rent values. This result supports the theory by Zhou (2019), where the researcher implements the decision tree in predicting and analysing the rental rates but for housing purposes. Hence, this research proved that the decision tree model could be implemented to analyse real estate property involving rent values. The finding also implies that amenities and in-house services are the most significant factors influencing office building rental. The results aligned with the theories stated by Bera (2019) that signifies the amenities and in-house services will contribute to determining office rent. Besides, the generated results somehow identify that macroeconomic determinant such as Gross Domestic Product (GDP) and inflation does not show any effect on office rent, and this is perceived from the generated results by the three (3) different types of models 1) Decision Tree, 2) Random Forest, and 3) Support Vector Machine used in predicting office rent values. As a recommendation, future research should focus on the effect of macroeconomic factors on office rents, such as lending rates, interest rates, stocks, and GDP. It is crucial since office demand plays an essential role in urban development, demand analysis, new office investments, and planning strategies to benefit investors, urban planners, and policymakers.

6.0 Conclusions

The findings of this research have several applications for industry and research. The adaptations of Machine Learning will greatly assist professional bodies, for instance, the Local Authorities, the Economic Planning Unit and Board of Valuers, Appraisers, Estate Agents, and Property Managers (BOVAEA), in commercial office building development and to use the model in revaluation exercise to garner higher revenues. The result will provide additional knowledge on factors influencing a new model for predicting office building rental, especially for new projects. Industry practitioners are encouraged to apply this Machine Learning Model during their practice to demonstrate the transacted rent since the model has been tested and can predict rents, requires less coding, more flexible. It is a fast method of assessing rents that will facilitate and streamline the use of market rental as an acceptable valuation base for all states in Malaysia.

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