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GREEN BUILDING VALUATION BASED ON MACHINE LEARNING ALGORITHMS

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Abstract

In the cycle of Industrial Revolution 4.0 (IR 4.0), many issues in the industries can be solved with implementation of artificial intelligence approaches, including machine learning models. Designing an effective machine learning model for prediction and classification problems is a continuous effort. In addition, time and expertise are important factors needed to adapt the model to a specific problem such as green building housing development. Green building is known as a potential method to improve building performance efficiency. To our knowledge, there is still no implementation of machine learning models on green building valuation features for building price prediction compared to conventional building development. This paper provides an empirical study report, that building price predictions are based on green building and other general determinants. This experiment used five common machine learning algorithms namely 1) Linear Regressor, 2) Decision Tree Regressor, 3) Random Forest Regressor, 4) Ridge Regressor and 5) Lasso Regressor tested on a real estate data-set of covering Kuala Lumpur District, Malaysia. 3 set of experiments was conducted based on the different feature selections and purposes The results show that the implementation of 16 variables based on Experiment 2 has given a promising effect on the model compare the other experiment, and the Random Forest Regressor by using the Split approach for training and validating data-set outperformed other algorithms compared to Cross-Validation approach. The research will provide an appropriate model in predicting the price of a green building which is beneficial to the government agencies and industry practices

Keywords: *machine learning model; algorithm; green building; property features*

1.0 INTRODUCTION

The green building can be defined as the approach that enhances the efficiency performance of the building and sites using energy, water and natural materials. It can reduce the negative impact on human, environment and health by improving the operation of system, maintenance, design of a building, the construction and relocation of a longer building life cycle (MGBC, 2019; Ojo-Fafore et al., 2018; Uparwat et al., 2012).

In real estate industry, there are several “conventional methods” in valuation, which are commonly used to determine property price. These methods are comparison method, investment method, residual method, profit method, cost method and Discounted Cash Flow (DCF) (Malaysian Valuation Standard, 2019) . However, all of these methods have their own limitations to different types of property categories (Pagourtzi et al., 2003; Pitts & O.Jackson, 2008). To highlight, evidence from several cohort studies suggests that there is no definitive evidence for the latest and most appropriate evaluation method for the green building types although conventional methods may be applied (Del Giudice & De Paola, 2016; Lee et al., 2018; Mattia et al., 2018; Nejad et al., 2017; Pagourtzi et al., 2003). Therefore, it is important for the author to find a more reliable method of predicting prices for this type of green building. Along with that, new methods and techniques have been discovered such as the machine learning models.

However, despite the rapid use of machine learning in building price predicting and valuation, there is no direct study that investigates the price of green building based on machine learning model. To our knowledge, previous reports related to property valuation have been conducted on many aspects of prediction without green building elements such a as conventional building (Borde et al., 2017; Ma et al., 2018; Shinde and Gawande, 2018; Valle, 2016) property pricing appraisal research (Chaphalkar and Sandbhor, 2013; Tabales et al., 2013; Rahman et al., 2019) real estate price prediction cases (Chen et al., 2017; Lin & Chen, 2011; Mu et al., 2014), price prediction of apartment (Čeh et al., 2018; Oladunni and Sharma, 2017), land appraisal under Geographic Information System (Yalpir & Unel, 2017) energy consumption of commercial building based on gradient boosting model (Touzani et al., 2018).Given this situation, machine learning is a model that is so promising in solving this kind of problem and has been proven effective in various predictions and classification problems(Kaytan & Aydilek, 2017) . However, the accuracy of the results produced by the model is highly dependent on many factors including the algorithms, hyper-parameters tuning and different groups of features selection.

Therefore, this paper was written with the aim of reporting the design and implementation of machine learning models based on the auto hyper-parameters tuning and different feature selection groups. The focus is on predictive matter because the author intends to predict the prices of green buildings. The structure of this paper is as follows. Part II focuses on the research background related to machine learning in real estate and potential use. Part III describes the research methodology followed by a discussion of the result in Part IV. The closing remarks are written in the last part.

2.0 RESEARCH BACKGROUND

2.1 Machine learning in Real Estate Valuation

Machine Learning Model has been used in other disciplines such as business, computer engineering, industrial engineering, bioinformatics, medical, pharmaceuticals, physicals, and statistics to gather knowledge and predict future events (Singh et al., 2007). With the recent growth in the real estate market, Machine Learning plays an important role to predict the price of a property. However, few researchers have experimented on the selling price for real estate properties using Machine Learning (Borde et al., 2017; Shinde & Gawande, 2018). But none of the studies reported the use of this method in condominium green building studies.

The Machine Learning Model which are commonly used in real estate studies in predicting the real estate price are Linear Regression (Borde et al., 2017; Dimopoulos et al., 2018; Wezel & Potharst, 2005), Decision Tree (Baldominos et al., 2018; Ma et al., 2018; Shinde & Gawande, 2018; Wezel & Potharst, 2005), Random Forest (Borde et al., 2017; Lee et al., 2018; Valle, 2016), Ridge Regression (Xin & Khalid, 2018) and Lasso Regression (Lu et al., 2017; Shinde & Gawande, 2018), Support Vector Machine, Neural Network (Borde et al., 2017; Dimopoulos et al., 2018; Xin & Khalid, 2018). The basic function of all these algorithms is to accurately predict the price of real estate data-set.

2.2 Potential Use of Machine Learning Model in Real Estate Market

Accurate evaluation of property price is crucial for real estate, the stock market, tax sector, the economy and the power of purchasers (Pagourtzi et al., 2003). The conventional method is limited to the scope of current systems data and therefore, it needs to be reconsidered. Normally, predicting a property price is often done through basic comparative market analysis as well as similar real estate in the same area to provide an approximate price for a particular property (Kummerow, 2003). However, in green building context, the other features that can contribute or give positive impact or added values to the green building price should also be considered to produce an accurate result in the price and to reflect the current market value (Abdullah & Mohd, 2018). This will only happen if the valuer considers other features that influence the green building price.

Machine learning models are seen to have the potential in considering those features and problems. By considering the other features in predicting the price of green building using the Machine Learning Model, the price produced will be more accurate and reflects the current market value. Predicting the accurate price of green property in certain areas might be able to help the country, government and the owner of the property in decision making, such as maintenance purpose and preservation. This is a huge benefit for investors and property developers to get your vendor a better price.

3.0 METHODOLOGY

3.1 Dataset

This dataset is a collection of green Building housing prices in 2018 for condominium type property with seventeen features from the Valuation and Property Department (JPPH). Table 1 shows a set of features used to develop the machine learning model with Transaction Price as the Dependent Variable.

Table 1: Features In the dataset

Features	Description
Transaction Price	Dispose price/sqf (RM)
Date of Transaction	Building Transaction/Months
MFA	Main Floor Area
Lot area	Lot area
Tenure	Freehold/Leasehold
Type of Property	Residential/Commercial
No of bedroom	Number of bedrooms
Level Property	Level Property Unit
Floor	Building Floor
Building Façade	City/Park/Lake/Klcc
Age of Building	Age of Building
Distance	Distance to Central Business District
Accessibility	Ease of accessibility
Mukim	Mukim
Certificate	Green Certificate
Density	Population Density
Security	Security of Building
Infrastructure	Infrastructure Development

Sources: Researcher (2020)

3.2 Features Selection

Features are the variables used for the machine learning Model. Feature selection is the identification of which variables to use as the Independent Variable (IV) for the model. The author has reported that the performances of machine learning can be influenced by the features of the model (Abuzneid et al., 2018; Langley, 1994) One of the basic techniques for features selection refers to the correlation among the variables of the IVs (Hall, 1999).

In this research, different feature selections were executed in different sets of experiments based on the purposes as illustrated in Figure 1 below. The identification of the security building features is the most influential in determining the price of green building based on the results of correlation and Multiple Linear Regression model in the SPSS Software.

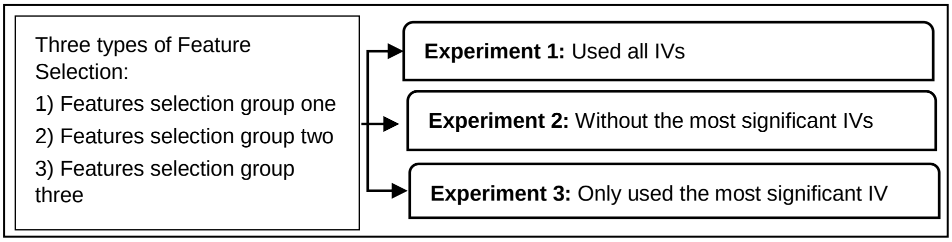

Figure 1: Difference features of phyton program

Sources: Researcher (2020)

As example, Figure 2 shows the features (Transaction Price) that were not used for the features can be dropped in Machine learning. Figure 2 shows the features selection for Experiment 1.

```
X_train=training.drop([“TransactionPrice”], axis=1.values.
Y_train= training([“TransactionPrice’].values
X_test=testing..values.
Y_test=testingprice[“TransactionPrice”].values.
```

Figure 2: Used all IV

Sources: Researcher (2020)

3.3 Machine learning Algorithms with Auto-Hyper Parameter Tuning

This research used Python Sklearn Library and one of the advantages of using the Python Sklearn, is this library has the function of Auto Hyper-Parameters Tuning. This function will help the author to get the most optimal Hyper-Parameters setting through the process that is known as parameters optimization. Before validating the prediction, result of five common algorithms were used in this study namely Linear Regressor, Random Forest Regressor, Decision Tree Regressor, Ridge and Lasso, A suitable parameter configuration is identified first based on the training data-set by calling the *“best_estimator” approach*. This approach is provided in the Phyton Sklearn library to conduct the grid search optimization of hyper-parameter tuning on the given Machine learning algorithms. This is a useful way for unexpected data scientists to obtain parameter configuration suggestions for a model. To summarize, below are the steps of implementing the auto Hyper-Parameters tuning:

1. Call the Regressor algorithm.
2. Create a dictionary and define parameters for the algorithm with the corresponding set of values.
3. Call the grid search method by passing the created dictionary. Grid search is the model for auto hyper-parameters optimization used in the Sklearn auto approximation.
4. Do preliminary training for the algorithm with the grid search instance and get the parameters estimator.
5. Set the algorithm with the suggested parameters and conduct another fitness with the parameters.
6. Perform another training with the suggested parameters.
7. Validate the prediction value produced by the algorithm and get the score.

3.4 Training and Validation Set

It is a common practice to split the training dataset with the validation dataset. In this study. The separation has been aligned to 80:20 ratio of training and validation sets by using two training approaches which is Split and Cross-Validation. The experiment codes were developed with Pyhton 3.6 Jupyter Notebook platform and implemented in the processor of Intel i7 7th Generation processor, 16 GB RAM. Each model ran five experiments and the average results of metrics were calculated for comparison. The metrics to present the performances of Machine learning algorithms are R squared (R^) and root mean squared error (RMSE). The R^ can explain how well the selected features in predicting the dependent variable while RMSE represents the sample standard deviation difference between the predicted and real values. The range of values for R^ is between 0.1 and higher is better. Meanwhile, RMSE with lower value shows lower errors or differences in the prediction results.

4.0 RESULT

The results are presented in different tables according to the three groups of features selection namely Used all IVs, without the security building features and only used the security building features.

The average results from the five experiments of each machine learning model were calculated and recorded. The results of R^2 and RMSE for features selection Group One have considered all the 17 variables for the Machine learning algorithms are depicted according to the two training approaches as seen in Table 2.

Table 2: Accuracy results of the five machine learning algorithms with features selection group one

No	Algorithm	Split		Cross-Validation	
		R^2	RMSE	R^2	RMSE
1	Random Forest Regressor	0.962	393892.1	0.663	1010579.0
2	Decision Tree Regressor	0.894	664294.1	0.721	918429.4
3	Linear Regressor	0.885	504882.2	0.480	1254698.0
4	Ridge Regressor	0.796	921761.2	0.445	1296588.0
5	Lasso Regressor	0.781	954258.9	0.413	1332991.0

Sources: Researcher (2020)

All five algorithms generated better results with the split training approach and the outperform algorithm is Random Forest Regressor. This can be presented by the highest R^2 value 0.962 of the model, which implies the relationship between all the 17 features and the target price that can be accounted for by the Random Forest Regressor with 96% of the variation. Additionally, the model of Random Forest Regressor with Split training approach achieved the best accuracy result with the lowest error value presented by the RMSE (393892). This is followed by Decision Tree Regressor as the second-highest model. The third highest coefficient of R^2 is 0.885 under Linear Regressor. Meanwhile, Ridge Regressor has the second lowest of R ^ 2 value 0.796 with the highest of RMSE 921761.2. Finally, Lasso Regressor has the lowest R ^ 2 value and the highest RMSE.

The following Table 3 presents Feature Selections of Group Two that take into consideration all 16 variables to develop the Machine learning Regressor Models. The 16 variables were not inclusive of the variable namely security of building.

Table 3: Accuracy result of the five machine learning algorithm with features selection group two

No	Algorithm	Split		Cross-Validation	
		R^2	RMSE	R^2	RMSE
1	Random Forest Regressor	0.963	389249.3	0.629	1059404.0
2	Decision Tree Regressor	0.905	627070.4	0.363	1389184.0
3	Linear Regressor	0.848	580528.2	0.317	1438139.0
4	Ridge	0.731	1058462.0	0.307	1448546.0
5	Lasso	0.715	1090277.0	0.255	1502699.0

Sources: Researcher (2020)

Similarly, the Random Forest Regressor algorithm with the split approach for training and validating data-set outperformed other models compared to Cross-Validation approach. However, R^2 and RMSE values for Random Forest Regressor are slightly better than the value in Table 2. Meanwhile, the performance of Decision Tree Regressor increased when it was only dependent on the features without the building security. Furthermore, not much difference could be seen from the other model.

Lastly Table 4 lists the result of Features selection Group Three which only considered one variable, which is the building security.

Table 4: Accuracy of result from the five machine learning algorithms with features selection group three

No	Algorithm	Split		Cross-Validation	
		R^2	RMSE	R^2	RMSE
1	Random Forest Regressor	0.215	1808990.0	0.084	1666258.0
2	Decision Tree Regressor	0.242	1777426.0	0.107	1644604.0
3	Linear Regressor	0.076	1434889.0	0.107	1644604.0
4	Ridge	0.237	1783934.0	0.108	1643834.0
5	Lasso	0.242	1777430.0	0.107	1644604.0

Sources: Researcher (2020)

The implementation of only buiding security features into the model do not show a significant increase in each of the test models. All results are lesser than the results obtained from the experiment of Group One and Group Two. Thus, this experiment from Group Three will not be compared for testing the prediction prices of Green Building condominium.

5.0 CONCLUSION

Within the scope of this research, the implementation of 16 variables could increase the price of green building based on Experiment 2 which showed that green building condominium prices produce better value without the use of building security features compared to Experiment 1) with 17 variables. This can be determined by R^2 result by looking at the difference between R^2 of Experiment 1 and Experiment 2. Moreover, the worst results of all algorithms were produced by the model with single building security features. It can be concluded that the building security features do not significantly affect the model performances. Although, the result of Multiple Linear Regression Model states that building security is a major feature that affects green building price. Furthermore, among the five selected Machine Learning algorithms, the author decided to choose Random Forests Regressor algorithms as it presented the best performances by using the Split approach for training and validating data-set. However, the finding is limited to the tested dataset and therefore requires further investigations for different perspectives of Green Building in future studies.

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2. Adalah dimaklumkan bahawa pihak kami ingin memohon kelulusan tuan untuk mengimbas (*digitize*) dan memuat naik semua jenis penerbitan di bawah UiTM Cawangan Perak melalui Repositori Institusi UiTM, PTAR.

3. Tujuan permohonan ini adalah bagi membolehkan akses yang lebih meluas oleh pengguna perpustakaan terhadap semua maklumat yang terkandung di dalam penerbitan melalui laman Web PTAR UiTM Cawangan Perak.

Kelulusan daripada pihak tuan dalam perkara ini amat dihargai.

Sekian, terima kasih.

Setuju.

"BERKHIDMAT UNTUK NEGARA"

27.1.2023

Saya yang menjalankan amanah,

PROF. MADYA DR. NUR HISHAM IBRAHIM
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SITI BASRIYAH SHAIK BAHARUDIN
Timbalan Ketua Pustakawan

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