UNIVERSITI TEKNOLOGI MARA
Cawangan Perak
Kampus Seri Iskandar

e-Proceeding

v-GOGREEN2020 29 - 30 SEPT

VIRTUAL GO-GREEN: CONFERENCE & PUBLICATION

"SUSTAINABLE ENVIRONMENT, RESILIENCE AND SOCIAL WELL-BEING"

Organiser :
Research, Industrial Linkages, Community & Alumni Network (PJIM&A)

Co-organiser :
Faculty of Architecture, Planning and Surveying (FSPU) & Centre for Post Graduate Studies (CGS)

Publication Date : 22nd February 2021

Virtual Go-Green Conference and Publication 2020

UNIVERSITI TEKNOLOGI MARA, PERAK BRANCH
February 2021

Editors

Dr Junainah Binti Mohamad
Nurulanis Ahmad @ Mohamed
Jannatun Naemah Binti Ismam
Najma Binti Azman

Chief Language Editor

Dr Hjh Shazila Abdullah

Language Editors

Dr Daljeet Singh Sedhu A/L Janah Singh
Zarlina Mohd Zamari
Mary Thomas
Iza Faradiba Mohd Patel
Farahidatul Akmar Awaludin
Wan Faridatul Akma Wan Mohd Rashdi
Wan Nurul Fatihah Wan Ismail
Nazirul Mubin Mohd Noor
Noor Aileen Ibrahim
Jeyamahla Veeravagu
Noraini Johari
Hajah Norakmarwati Ishak

Panel of Reviewers

Dr Asniza Hamimi Abdul Tharim
Ar Iznny Ismail
Dr Azizah Md Ajis
Ar Jamaludin Bin Hj Muhamad
Ar Azman Bin Zainonabidin
Sr Ts Dr Asmat Binti Ismail
Dr Siti Norsazlina Haron
Sr Dr Norazian Mohamad Yusuwan
Dr Raziah Ahmad
Dr Asmalia Che Ahmad
Wan Norizan Wan Ismail
Sr Dr Kartina Bt Alauddin
Dr Norehan Norlida Bt Mohd Noor
Assoc Prof Dr Siti Akhtar Mahayuddin
Ts Siti Nur Aishah Mohd Noor
Sr Dr Nor Suzila Lop
Dr Hajah Norakmarwati Ishak
Assoc Prof Gs TPr Dr Halmi Bin Zainol
Dr Syed Ahmad Qusoiri Bin Syed Abdul Karim
Sr Dr Anis Sazira Binti Bakri
Dr Kharizam Binti Ismail
Dr Izatul Farrita Mohd Kamar
Siti Hasniza Rosman
Dr Izatul Laili Jabar
Sr Nurul Fadzila Zahari
Sr Dr Irwan Mohammad Ali
Shazwan Mohamed Shaari
Ir Dr Amirul Bin Abd Rashid
Sr Dr Alia Abdullah Saleh
Dr Anis Syazwani Binti Sukereman
Dr Nor Aini Salleh
Mohamad Haizam Mohamed Saraf
Sr Nurul Sahida Fauzi
Sr Dr Muhammad Azwan Sulaiman
Assoc Prof Sr Dr Rohayu Ab Majid
Sr Dr Nor Nazihah Bt Chuweni
Sr Dr Natasha Khalil
Dr Ida Nianti Mohd Zin
Nur Idzhainee Hashim
Sr Ts Dr Mohamad Ridzuan Bin Yahya
Sr Gs Noraain Binti Mohamed Saraf
Sr Dr Ani Saifuza Abd Shukor
Ir Normadyzah Ahmad
Sr Gs Dr Abdul Rauf Bin Abdul Rasam
Norhayati Talib
Sr Dr Raha Sulaiman
Ts Dr Izham Abdul Ghani
Dr Nur Huzeima Mohd Hussain
Assof Prof Ts Norhafizah Abdul Rahman
Dr Siti Rasidah Md Sakip
Dr Muhamad Hilmi Mohamad @ Masri
Dr Zakaria Hashim
IDr Dr Nadiyanti Mat Nayan
Sr Nurulanis Binti Ahmad @ Mohamed
Gs Dr Nor Eeda Haji Ali
Gs Dr Nor Hisham Bin Md Saman

Graphic Designer

Farah Hanna Ahmad Fuad
Mohamad Shahin Bin Shahdan

Main Committee
Virtual Go-Green Conference and Publication 2020

Advisor 1	*: Prof Sr Dr Md Yusof Hamid, AMP*
Advisor 2	*: Assoc Prof Dr Nur Hisham Ibrahim*
Chairman	*: Sr Dr Asmalia Che Ahmad*
Co-Chairman	*: 1. Sr Dr Yuhainis Abdul Talib 2. Sr Dr Haryati Mohd Isa*
Treasurer	*: Mohamad Haizam Mohamed Saraf*
Secretary	*: Noorliza Musa*
Head of v-Conference	*: Sr Dr Nor Suzila Lop*
Head of e-Proceeding	*: Dr Junainah Mohamad*
Head of Scopus Indexed Journal Planning Malaysia Journal (PMJ)	*: Assoc Prof Gs Dr Mohd Fadzil Abdul Rashid*
Head of Scopus Indexed Journal Malaysian Construction Research Journal (MCRJ)	*: Sr Dr Natasha Khalil*
Head of Paper Reviewer	: *Dr Asniza Hamimi Abdul Tharim*

Committee Members
Virtual Go-Green Conference and Publication 2020

E-Proceeding Paper Reviewer

Noraini Md Zain
Shafikah Saharuddin
Nur Fatiha Mohamed Yusof
Farrah Rina Mohd Roshdi

E-Proceeding Formatting

Nurulanis ahmad @ Mohamed
Jannatun Naemah Binti Ismam
Najma Binti Azman

E-Proceeding Language Reviewer

Dr Hjh Shazila Abdullah
Dr Daljeet Singh Sedhu A/L Janah Singh
Zarlina Mohd Zamari
Dr Mary Thomas
Iza Faradiba Mohd Patel
Farahidatul Akmar Awaludin
Wan Faridatul Akma Wan Mohd Rashdi
Jeyamahla Veeravagu
Wan Nurul Fatihah Wan Ismail
Nazirul Mubin Mohd Noor
Noor Aileen Ibrahim
Noraini Johari
Dr Hajah Norakmarwati Ishak

Virtual Conference

Norazlin Mat Salleh	*Registration*
Shahela Mamter	*Auditor*
Mohd Esham Mamat	*Auditor*
Noor Anisah Abdullah @ Dolah	*Auditor*
Mohamad Tajudin Saidin	*Certificate & Conference Kit*
Fairiz Miza Yob Zain	*Logistic*
Mohd Firdaus Zainuddin	*Logistic*
Farah Hanna Ahmad Fuad	*Promotion & Publicity*
Mohamad Shahin Shahdan	*Promotion & Publicity*
Mohd Asrul Hassin	*Liason Officer*

Organiser:
Research, Industrial Linkage Community and Alumni Network Office (PJIM&A)
Universiti Teknologi MARA, Perak Branch, Seri Iskandar.
Malaysia

Co-Organiser:
Faculty of Architecture, Planning and Surveying (FSPU)
and,
Centre for Post Graduate Studies (CGS)
Universiti Teknologi MARA, Perak Branch, Seri Iskandar.
Malaysia

e ISBN 978-967-2920-06-9

9 7 8 9 6 7 2 9 2 0 0 6 9

Copyright © Research, Industrial Linkage Community and Alumni Network Office (PJIM&A), Faculty of Architecture, Planning and Surveying (FSPU) and, Centre for Post Graduate Studies (CGS). All rights reserved. No part of this publication may be produced, stored in a retrieval system, or transmitted in any form or by means electronics, mechanical, photocopying, recording or otherwise, without prior permission in writing from the publisher

APPLICATION OF MACHINE LEARNING IN ANALYSING HISTORICAL AND NON-HISTORICAL CHARACTERISTICS OF HERITAGE PRE-WAR SHOPHOUSES

Nur Shahirah Ja'afar [1], Junainah Mohamad [2]
[1]*Faculty of Architecture, Planning and Surveying, Universiti Teknologi MARA Shah Alam, Malaysia*
[2]*Department of Estate Management, Faculty of Architecture, Planning and Surveying, Universiti Teknologi MARA, Perak Branch, Seri Iskandar Campus, Seri Iskandar, 32610 Perak, Malaysia*

Abstract

Real estate is complex and its value is influenced by many characteristics. However, the current practice in Malaysia shows that historical characteristics have not been given primary consideration in determining the value of heritage property. Thus, the accuracy of the values produced is questionable. This paper aims to see whether the historical characteristics give significance values toward shophouses at North-East of Penang Island, Malaysia. Several Machine Learning algorithms have been developed, namely Random Forest Regressor, Decision Tree Regressor, Lasso Regressor, Ridge Regressor and Linear Regressor. The result shows that the Random Forest Regressor with historical characteristics is the best fitting model with higher values of adjusted R-Squared (R^2) and lowest value of Root Mean Square Error. This indicates the historical characteristics contribute to the significance value of heritage property. By considering historical characteristics, it can contribute to the accuracy of the value predicted.

Keywords: *pre-war shophouse; machine learning; historical characteristics; random forest (RF); price prediction*

1.0 INTRODUCTION

In 2008, George Town Penang Island Malaysia was recognized as Historic City that was inscribed by UNESCO World Heritage Site (Azizan et al., 2020). This recognition was given because of the presence of the diversity of tangible and intangible heritage around the George Town area. This paper study on the cultural heritage site which is re-war shophouses and it is located within the core and buffer zone in George Town. As this subject property is labelled as a tangible cultural heritage, it has the value of historical significance. Hence this leads to several measures that should be considered to conserve and preserve this heritage property as a part of economic indicator. According to Ruijgrok, (2006) the preservation of cultural heritage does not only have costs but also produce benefits such as economic and financial value. When assessing the economic value of cultural heritage sites, it is known as total economic value which consists of use-value and non-use value (Daneshdoust, 2015; Mohamad et al., 2014). In economic value, the heritage pre-war shophouses have a use value because it is a private property. Besides, it gives the benefits to the owner which means from the direct consumption of property (SGS Economics and Planning, 2017).

In real estate valuation, valuing heritage property is important to estimate the possible value of property to achieve the accurate value (Mohamad et al., 2019). In a study by Mohamad et al., (2020), it was stated that the accurate value of heritage property would help in better decision making' t Thus, others would appreciate, acknowledge and assist the management of heritage property to produce a proper and reliable method of valuation for heritage property. Mohamad et al., (2019) has recommended one of the steps to be considered in enhancing the heritage property method to establish a proper, historical characteristic in valuing heritage property. Mohamad, et al., (2014) questioned the proper historical characteristics, Studies by Mohamad, et al., (2017) mentioned a few characteristics influencing the value of heritage property such as property transaction characteristics, structural characteristics and historical characteristics. In a study by Ja'afar et al. (2020) historical characteristics were applied in estimating the value of heritage property using multiple regression analysis and this shows that the characteristics can be considered. To compensate for the lack of literature on historical characteristics and other related criteria, researchers have collected several historical characteristics from National Property Information Centre (NAPIC), George Town World Heritage Incorporated (GTWHI) and site inspection. This study intends to look if historical characteristics by valuers are similar with the current historical characteristics through the publication of a book imposed by (George Town World Heritage Site Incorporated, 2016). Thus the effort wiillreview and restore the latest recognition of historical characteristics areas for improvement of their special significance (Forbes et al., 2014).

From the previous studies, several methods have been used in estimating the value of heritage property such as sale comparison method, cost method, contingent valuation method and regression model (Mohamad et al., 2020; Ruijgrok, 2006). Nevertheless, there is no solid evidence of a proper valuation method for heritage property (Mohamad et al., 2020). Besides, the studies that compared several approaches such as multiple regression analysis, rank transformation regression and contingent valuation method by Mohamad (2012) need to be studied in depth due to the different functions and variables used in these methods. Currently, the most popular statistical technique used is Machine Learning. Itwas used in various fields including real estate industry (Cano, et al., 2020; Conway, 2018; Fiorucci et al., 2020; Phan, 2019). Mohamad et al. (2020) also stated that most studies had identified housing as the most common typ of property used in valuing using Machine Learning, but none of the studies were from Malaysia. Moreover,the study on heritage property using machine learning technique are still undiscovered yet. To study the heritage property characteristics, researchers has focused in investigate the historical characteristics with non-historical characteristics using Machine Learning technique. According to Baldominos et al. (2018), through the use of machine learning, the hidden value in a data source can be analyzed to derive actionable insights from the data. The application of machine learning also can identify more opportunities in the real estate market. Besides, this would make real estate investors realize to give more insight into a property's surroundings.

This is an attempt to identify among the physical aspects of heritage property, which characteristics are significant and should be considered in heritage property valuation. This paper is arranged in five sections, starting with an introduction by considering fundamentals involved in this study. The second wsection is on the background research w. Next, the methodology used in modelling, using Machine Learning technique, while the fourth shows the result of modelling and ends with the conclusion. was the conclusion. From the study, this paper reflects the concerns in considering historical characteristics in the community which involve professional property practitioners in deciding which approaches to deal with heritage property. Heritage valuation is one of the pathways to generate the value of heritage properties.

2.0 BACKGROUND OF STUDY

2.1 Heritage

According to National Heritage Act 645 (2005) the generic meaning of "heritage" refers to sites, objects and underwater cultural heritage. This paper study on the Heritage pre-war shophouses which was labelled as cultural heritage. There are varieties meaning of cultural heritage, as defined by Gabriel (2020) who stated it as handiwork of human deemed worthy of preservation and it can be tangible or intangible. Thus,pre-war shophouses is known as tangible cultural heritage because National Heritage Act 645 (2005) has listed an area, monument or building in this category as tangible cultural heritage. The recognition by UNESCO on Pre-war shophouses building located within George Town as a World Heritage

Site is due to the groups of buildings in that area which have the criteria mentioned in the Outstanding Universal Value (OUV). According to Azizan et al., (2020); Foo et al., (2018); Mustafa et al., (2017); Rahman, (2018); Shamsuddin et al., (2012) the criteria exists in George Town such as (ii) represent the multi-cultural trading town which involved Malay, Chinese, Indian and European cultures with different architecture, technology and monuments art: (iii) represent multi-cultural traditional living influences nor tangible or intangible besides the existence of different religious buildings, languages, foods, daily life, ethnics and (iii) the existence reflection of various architecture cultural from Malay Archipelago, India, China and Europe by the presence of unique building type and cultural.

2.2 Machine Learning

Machine Learning has become a popular programming practice among researchers to solve problems by predicting the current existing data which are gathered from the past data records (Milutinovic, 2019). There are two types of categories in solving problems using Machine Learning, which is supervised learning and unsupervised learning algorithms (Fiorucci et al., 2020; Lindholm et al., 2019). Within these categories, the most commonly used is supervised learning algorithms (Horino, et al., 2017). This supervised learning is used to predict an outcome from a given input and use the examples of the input or output pairs and it requires human work to create a training set to build the process of Machine learning algorithms. Unsupervised learning algorithms are different because they have no known output and no instructor to instruct the learning algorithms, in other words to extract information from the input data to build algorithms (Muller et al., 2017).

The Machine Learning approach has been used in the real estate field since a few years ago. It was used to find the market value of the building, predicting the long term value, profile matching, generating real estate listing and other information related to property forecasting (Phan, 2019). However, in Malaysia, the use of Machine Learning approach in the real estate field has not been used. Hence, the researcher would like to apply it as a price prediction in order to ascertain any benefits that could be obtained from it. There are five most common algorithms used in real estate analysis such as Random Forest, Decision Tree, Linear Regression, Lasso and Ridge (Mohamad et al., 2020).

According to Mohamad et al. (2020), the most supervised machine learning algorithm was nominated as successful in studies is the Random Forest (RF) algorithm. RF is also known as one of the ensemble learning and it can be used in classification and regression problem methods. It is usually use as decision making in real estate to predict the price of housing (Horino et al., 2017; Trawiński et al., 2017). In RF it has DT collection known as "Forest", but RF generalizes better than DT in improving the accuracy by selecting the highest votes (Fiorucci et al., 2020)

Next is Linear Regression (LR) algorithm which is known as ordinary least square (OLS) (Varma et al., 2018). LR was used to estimate values such as cost of houses, total sales and number of calls. There are two types of LR which are simple linear regression (SLR) and multiple linear regression (MLR). SLR uses one independent variable while MLR is considered when there are more than one independent variables. Basically, LR is applied for prediction, forecasting and studying the relationship between two variables (Borde, et al., 2017). LR equation is: $Y = a + ßx$. Where Y market price of property (predictive variable), x is a given input (predictor variable) (Oladunni et al., 2015).

Next, the Decision Tree (DT) algorithm can be used in classification and regression problems but mostly it is used for classification. It is used to visualize decision making. Commonly, it used to select variables, to access the significant connection of variables, to monitor missing values, prediction data and management (Song et al., 2015).

Next is Lasso Regression algorithm. According to Shinde et al, (2018), Lasso is known as L1 regularization technique because it is one of the most powerful formula in regression, which works by reducing the error between predicted and actual observations. Last but not least is Ridge regression, a linear model for regression which uses the same formula used in predictions using OLS (Muller et al., 2017). This algorithm is able to fit an additional constraint namely called regularization during training data. Ridge regression is known as L2 regularization. This regularization avoid overfitting during training. After modelling, the evaluation formula (?) used to determine the performance metrics are root mean square error

(RMSE) and adjusted R-Square (R^2) to show the good values predicted by the algorithm performance (Mohamad et al., 2020).

3.0 METHODOLOGY

3.1 Dataset

The involved dataset was collected from NAPIC, GTWHI and site inspection. As the property is known as tangible cultural heritage, researchers have to differentiate between the historical characteristics and non-historical characteristics in modelling using Machine Learning to observe which variables could influence the value of heritage property price.

3.2 Selected Variables

To train the variables using Machine Learning, researchers have divided the variables into three groups which are called feature. These features were used to train the dataset to observe what outcome Machine Learning will produce at the end of the process. Table 1 below shows the feature groups.

Table 1: Features in machine learning

No	All Features	Historical Features	Non-Historical Features
1.	Transaction Price	Transaction Price	Transaction Price
2.	Year of transaction	Year of transaction	Year of transaction
3.	Road	Road	Road
4.		Storey	Storey
5.	Land Area	Land Area	Land Area
6.	Main Floor Area	Main Floor Area	Main Floor Area
7.	Roof Material	Roof Material	Position
8.	Floor Material	Floor Material	
9.	Wall Material	Wall Material	
10.	Ceiling Material	Ceiling Material	
11.	Maintenance Outside	Maintenance Outside	
12.	Maintenance Inside	Maintenance Inside	
13.	Multifunction	Multifunction	
14.	Five-Foot Way	Five-Foot Way	
15.	Architectural Functionalistic	Architectural Functionalistic	
16.	Historical Styles	Historical Styles	
17.	Ensemble	Ensemble	
18.	Authenticity	Authenticity	
19.	Position		

3.3 Models Configuration

As mentioned earlier, this paper will predict an outcome from the given variables. Here researchers want to observe which features could influence the value of property price by evaluating using performance metrics. Thus, the Machine Learning model was built from the given features into training sets before evaluating the models. This model involved several processes (Refer to Figure 1).

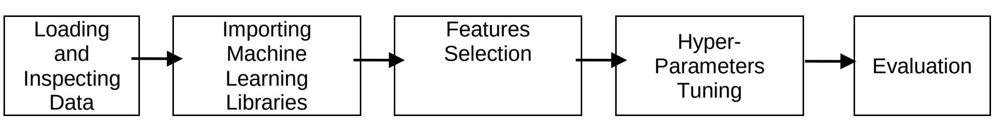

Figure 1: The configuration in modelling of machine learning algorithms

According to Figure 1 above, there are five processes of modelling Machine Learning in this paper. The first was started by loading and inspecting data which the researchers have to upload files containing data using format csv for inspecting the data in Python platform.

Second, researchers have to import Machine Learning libraries by calling Sklearn or known as Scikit-Learn library, which is one of Python' s most popular libraries (Igual et al., 2019). This library provides a simple and efficient module besides supporting Machine Learning algorithms. The library will then be synchronized with the uploaded data for the next step. The third process was feature selection; the selected features are shown in Table 1. Researchers have divided variables into three features, which are, (1) All feature (2) Historical feature (3) Non-Historical feature. The implementation of different features is to observe which variables influence the value of property price. Fourth will be the process of Hyper-Parameters Tuning, through the use of Sklearn library researchers can apply Auto Hyper-Parameter Tuning by call *"best_estimator"* to help in optimizing configuration in tuning. Last but not least is the evaluation process, this process is to observe how well the Machine Learning algorithms perform on the features by analyzing on performance metrics of R^2 and RMSE. The result will show the selected algorithm by referring to the best performance metrics, refer to Table 2.

4.0 RESULT

After modelling the features, machine learning produced the result of features with selected algorithms. Each features were generating with the chosen algorithms and these algorithms were evaluated using performance metrics of adjusted R^2 and RMSE. Table 2 shows the result of features.

Table 2: The result of features used machine learning

No	Algorithm	All Feature		Historical Feature		Non-Historical Feature	
		R^2	RMSE	R^2	RMSE	R^2	RMSE
1.	Random Forest Regressor	0.927	209542.0	0.937	193968.8	0.840	310923.7
2.	Linear Regression	0.675	725676.8	0.675	725676.8	0.650	752585.4
3.	Decision Tree Regressor	0.655	456002.0	0.655	456002.0	0.616	481739.0
4.	Lasso Regressor	0.493	553223.7	0.493	553223.7	0.502	548568.8
5.	Ridge Regressor	0.462	570024.7	0.462	570024.7	0.484	558394.8

As presented in the above table, there are three different features, which are, "All Features", "Historical Features" and "Non-Historical Features". For the "All Features" performance metrics was the highest R^2 which is 0.927 while the lowest RMSE is 209542.0. So, the selected algorithm was Random Forest Regressor. Next, "Historical Features" performance metrics scored the highest R^2 at 0.937 while the lowest RMSE is 193968.0. In sum, Random Forest Regressor is nominated as the most suitable for this dataset. Lastly for "Non-Historical Features", the good performance metrics of adjusted R^2 and RMSE with 0.840 and 310923.7. But, Random Forest Regressor was the chosen outperformed algorithms. To conclude, Historical Features' ' performance metrics is better than the other features.

5.0 CONCLUSION

This study has applied five algorithms such as RF, LR, DT, Lasso and Ridge on the heritage property dataset. Within these algorithms, the findings showed the model which fit with the data condition in modelling was RF Regressor by observing the performance metrics of adjusted R^2 and RMSE. The best result of RF Regressor is from the historical feature or known as historical characteristics data based on the highest value of adjusted R^2 and lowest value of RMSE. The historical characteristics studied were collected from a book entitled "George Town Historic Cities of the Straits of Malacca Special Area Pelan" published by GTWHI, (2016) and Yeow, (2015). These books were supported by Pinang Island City Council, Penang Town and Rural Planning Department and World Heritage Organization (WHO). Other than that, certain historical characteristics was collected from site inspection and data heritage properties transaction from NAPIC. This study gave benefits to the owner and community on heritage value such as financial benefits to the owner of the property to generate income or value in sale and purchase by the historical characteristics of heritage property. For community benefits such defining the identity and cultural of the community. besides contributing to the preservation and conservation of historical characteristics. (Armitage et al., 2013).

ACKNOWLEDGEMENT

The researchers would like to express their gratitude to the National Property Information Centre (NAPIC) for providing the property heritage data in Penang Island, and also the Malaysian Ministry of Education (MOE) for funding this researcher (FRG: FRGS/1/2018/WAB03/UITM/03/1).

REFERENCES

Armitage, L., & Irons, J. (2013). The Values of Built Heritage. Journal of Property Management, 31(3), 246–259.

Azizan, M. A., Zulkepli, N. N., Desa, H., & Ishak, N. (2020). The Challenges in Conservation Practices in Malaysia: A Study in UNESCO Heritage Site, Georgetown, Penang, Malaysia. 2nd International Conference on Materials Engineering & Science, 1–2. https://doi.org/10.1063/5.0000425

Baldominos, A., Blanco, I., Moreno, A. J., Iturrarte, R., Bernárdez, Ó., & Afonso, C. (2018). Identifying Real Estate Opportunities Using Machine Learning. Journal of Applied Science, 8(2321), 1–23.

Borde, S., Rane, A., Shende, G., & Shetty, S. (2017). Real Estate Investment Advising Using Machine Learning. International Research Journal of Engineering and Technology (IRJET), 04(03), 1821–1825.

C. Muller, A., & Guido, S. (2017). Introduction to Machine Learning with Python: A Guide for Data Scientists (First Edit; D. Schanafelt, Ed.). New York City: O'Reilly Media Incorperated.

Cano, E. L., Alfaro-c, E., Garc, N., & Larraz, B. (2020). A Fully Automated Adjustment of Ensemble Methods in Machine Learning for Modeling Complex Real Estate Systems. Journal of Complexity, 2020.

Conway, J. (2018). Artificial Intelligence and Machine Learning: Current Applications in Real Estate by. Massachusetts Institute of Technology.

Daneshdoust, D. (2015). Value Assessment of Built Heritage: A Case Study of Ferdowsi Mausoleum. Journal of Cultural Heritage Management and Sustainable Development, 5(3), 263–273.

Fiorucci, M., Khoroshiltseva, M., Pontil, M., Traviglia, A., Del Bue, A., & James, S. (2020). Machine Learning for Cultural Heritage: A Survey. Journal of Pattern Recognition Letters, 133, 102–108.

Foo, R., & Krishnapillai, G. (2018). Preserving the Intangible Living Heritage in the George Town World Heritage Site, Malaysia. Journal of Heritage Tourism, 0(0), 1–13. https://doi.org/10.1080/1743873X.2018.1549054

Forbes, S., Goodhead, T., & Moobela, C. (2014). Life-Cycle Maintenance Cost Implications of Heritage Properties: Valuation Challenges and Opportunities for Further Research. FIG Congress 2014 Engaging the Challenges - Enhancing the Relevance, (June 2014), 1–12.

Gabriel, S. P. (2020). Making Heritage in Malaysia (First Edit; S. P. Gabriel, Ed.). Singapore: Springer Nature Singapore Pte Ltd.

George Town World Heritage Site Incorperated. (2016). George Town Historic Cities of the Straits of Malacca Special Area Plan (First; George Town World Heritage Site Incorperated, Ed.). George Town: State Government of Penang, PLANMalaysia@ Pulau Pinang, City Council of Penang Island and George Town World Heritage Incorperated.

Horino, H., Nonaka, H., & Claire, E. (2017). Development of an Entropy-Based Feature Selection Method and Analysis of Online Reviews on Real Estate. Journal of Industrial Engineering & Engineering Management, 2351–2355.

Igual, L., & Segui, S. (2019). Introduction to Data Science (A Python Approach to Concepts, Techniques and Applications). In I. Mackie (Ed.), Springer (First Edit).

https://doi.org/10.1201/9780429341830
Ja'afar, N. S., & Mohamad, J. (2020). An Assessment of Heritage Property Values using Multiple Regression Analysis: George Town, Penang Island. Malaysian Journal of Sustainable Environmen, 7(2), 37–60.
Lindholm, A., Wahlström, N., Lindsten, F., & Schön, T. B. (2019). Supervised Machine Learning (p. 56). p. 56. Uppsala University.
Milutinovic, M. (2019). Towards Automatic Machine Learning Pipeline Design. University of California, Berkeley.
Mohamad, J. (2012). Assessment of Property Values in Thin Market using Rank Transformation Regression and Multiple Regression Analysis. Universiti Teknologi Malaysia.
Mohamad, J., & Ismail, S. (2019). Capabilities of Revealed Preference Method for Heritage Property Valuation. Journal of the Malaysia Institute of Planners, 17(1), 377–379.
Mohamad, J., Ismail, S., Iman, A. H., & Mohd, T. (2017). Assessment of Heritage Property Values Using Multiple Regression Analysis and Rank Transformation Regression. Journal of Environment Behaviour, 207–219.
Mohamad, J., Ismail, S., & Rosdi, A. R. (2014). The Need to Improve Existing Method of Valuation for Cultural Heritage Asset. Journal of Heritage and Economics, 463–472. https://doi.org/10 14575/gl/heritage2014/00??
Mohamad, J., Ja'afar, S., & Ismail, S. (2020). Heritage Property Valuation using Machine Learning Algorithms. 26TH Annual Pacific Rim Real Estate Society Conference, (Cvm), 1–12.
Mustafa, S., & Saleh, Y. (2017). An Overview on Intangible Cultural Heritage in Malaysia. International Journal of Academic Research in Business and Social Sciences, 7(4), 1053–1059. https://doi.org/10.6007/ijarbss/v7-i4/2914
National Heritage Act 645. National Heritage Act 645., Pub. L. No. 645, 1 (2005).
Oladunni, T., & Sharma, S. (2015). Predictive Real Estate Multiple Listing System Using MVC Architecture and Linear Regression 1 Introduction.
Phan, T. D. (2019). Housing Price Prediction using Machine Learning Algorithms: The Case of Melbourne City, Australia. International Conference on Machine Learning and Data Engineering, 35–42.
Rahman, S. (2018). Emerging Built Heritage Commodification of Boutique Hotels in World Heritage Site: Evidence from George Town, Penang, Malaysia. Journal of the Malaysian Institute of Planners, 16(4), 104–116.
Ruijgrok, E. C. M. (2006). The Three Economic Values of Cultural Heritage: A Case Study in the Netherlands. Journal of Cultural Heritage, 7, 206–213. https://doi.org/10.1108/JCHMSD-05-2018-0032
SGS Economics and Planning. (2017). The Value of Heritage: Summary Report. Melbourne.
Shamsuddin, S., Sulaiman, A. B., & Amat, R. C. (2012). Urban Landscape Factors That Influenced the Character of George Town, Penang Unesco World Heritage Site. Procedia - Social and Behavioral Sciences, 50. 238–253 pp.
Shinde, N., & Gawande, K. (2018). Valuation of House Prices using Predictive Techniques. Journal of Advances in Electronics Computer Science, 5(6), 34–40.
Song, Y., & Lu, Y. (2015). Decision Tree Methods: Applications for Classification and Prediction. Journal of Biostatistics in Psychiatry, 27(2), 130–136.
Trawiński, B., Telec, Z., Krasnoborski, J., Piwowarczyk, M., & Talaga, M. (2017). Comparison of Expert Algorithms with Machine Learning Models for Real Estate Appraisal. Journal of Science and Technology.
Varma, A., Sarma, A., Doshi, S., & Nair, R. (2018). House Price Prediction Using Machine Learning and Neural Networks. Journal of Inventive Communication and Computational Technologies (ICICCT), 1936–1939.
Yeow Wooi, T. (2015). Penang Shophouses a Handbook of Features and Materials (First Edit; R. Gareth & G. Jenkins, Eds.). George Town: Tan Yeow Wooi Culture and Heritage Research Studio.

Pejabat Perpustakaan
Librarian Office

Universiti Teknologi MARA
Cawangan Perak
Kampus Seri Iskandar
32610 Bandar Baru Seri Iskandar,
Perak Darul Ridzuan, MALAYSIA
Tel: (+605) 374 2093/2453 Faks: (+605) 374 2299

اونيۏرسيتي تيكنولوݢي مارا
UNIVERSITI TEKNOLOGI MARA

Surat kami : 700-KPK (PRP.UP.1/20/1)
Tarikh : 20 Januari 2023

UNIVERSITI TEKNOLOGI MARA PERAK
TERIMA
2 5 JAN 2023
Tindakan
Universiti Teknologi MARA Perak
PEJABAT REKTOR

Prof. Madya Dr. Nur Hisham Ibrahim
Rektor
Universiti Teknologi MARA
Cawangan Perak

Tuan,

PERMOHONAN KELULUSAN MEMUAT NAIK PENERBITAN UiTM CAWANGAN PERAK MELALUI REPOSITORI INSTITUSI UiTM (IR)

Perkara di atas adalah dirujuk.

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
REKTOR
UNIVERSITI TEKNOLOGI MARA
CAWANGAN PERAK
KAMPUS SERI ISKANDAR

SITI BASRIYAH SHAIK BAHARUDIN
Timbalan Ketua Pustakawan

nar