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Predicting House Rental Value Among Students in Higher Institution Using Data Mining Techniques

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ABSTRACT

Rental housing value is a prominent issue among students in higher institutions especially those who stay off–campus as the stay off-campus figure has been increasing these past years. The aim of this research is to determine the students' perception on the level of agreement on potential factors (agreement on rental fee, socializing, housing facilities, privacy) that might affect the rental housing value. This study also examined the characteristics that determine the rental house value among university students. This study was conducted on 377 selected students from UiTM, UMK and USM in Kelantan, Malaysia. Stratified sampling was used to select the samples and cross-sectional study design was employed. The data was analysed using data mining approach of ID3 Decision Tree, CART Decision Tree and Neural Network classifier. The study found that facilities indicate the highest score of students' perception on the level of agreement of potential factors affecting rental housing value. Based on the predictive model, ID3 Decision Tree is the best model in determining the factors that significantly influence the rental value. The most important variable in determining the rental house value is whether the house is equipped with these three important facilities (microwave, single room and television) or not.

Keywords: House Rental, Data Mining, Facilities, Decision Tree

1 INTRODUCTION

The rapid growth of higher education institutions such as universities has shown a great impact to the expansion of student population in developed areas. The number of students' enrolment in Higher Education Institutions (HEI) had risen from 2,376,975 in 2016 to 2,751,865 in 2020 [1]. There is a global movement to increase students' opportunities to attend universities. The same pattern occurs in Malaysia as well. Malaysia is now one of the countries with a promising trend in the rise in the number of students attending universities and colleges year after year [2]. Educational statistics from the Ministry of Education of Malaysia indicate that the number of public university enrolments increased from 538,555 students in 2017 to 592,680 students in 2020 [3].

The impact of university presence can be seen in the local community and infrastructure development. Demand for student rental housing increases as the number of students studying at universities has risen. One of the student's fundamental demands is that the housing meets the need for shelter. Rental housing or "rental property" means a facility for rental housing that is leased or planned to be leased. Rental housing often implies a building to be used on a rental basis to provide living accommodation for individuals or families and to provide facilities such as dining kitchen, bedroom, entertainment or indoor games common room, first aid room, laundry, security guard room, and so on. Hartman [4] stated that having a healthy, convenient place to live for college or university students is an integral part of being able to concentrate and perform good in school. However, whether it is a convenient dorm on campus or an off-campus apartment, student housing poses obstacles that students need to weigh before choosing where to live each semester. Therefore, a student's decision to rent the house is affected by these factors.

Most universities failed to keep up with the growth of demand for student housing or hostels due to the overcrowding issue. This condition occurs when students' enrollment are more than the facilities provided to accommodate. This problem has been recognized as a worldwide issue and not a new concern in higher education. Overcrowding has put stress on facilities, as well as the teachers and students [5]. In Hongkong, China, the number of students increases because the government of Hongkong enacted several policies designed to attract students for employment and study. These students have begun to live off-campus as the capacity of student housing is limited [6]. However, in Bangladesh, some students decide to stay off-campus rather than staying on-campus due to desirability to fulfill housing demands and lifestyle [7]. Sulaiman [8] conducted a study in Kano, Nigeria, and the result showed that 60% of the enrolled students in Campus of Bayero University are living off-campus due to the inability of the university to accommodate the students, and provide access to facility, freedom etc. In Malaysia, to cater for such phenomenal growth in higher education institute, Universiti Teknologi MARA expended off-campus students to be registered under Non-resident (NR) unit [9]. Khozaei et al. [10] conducted a survey among public university students in Malaysia to identify their preference regarding residence hall design and the result showed that students prefer suite-style, single room with shared bathroom to traditional and double sharing room.

The value of the housing should be considered a condition that can fulfill the students' housing needs and meet certain basic requirements that are practically convenient for the student's daily standard of living [11]. The rental fee is the amount that the students should pay as tenants to the landlords. The rental fee mostly varies according to location as well as accommodation provided. Most of the students prefer housing with affordable value. However, rental fees may depend on location and house type including other factors like facilities provided or housing features [12]. Dasimah et al. [9] found that majority of local university students in Malaysia pay the second-lowest price monthly rental rate of houses at a range of RM100 to RM 149. Adama et al. [13] found that a great influence regarding residency factor is rent accommodation.

An important factor in the journey of college life as a student is building positive behaviour to develop relationships between friends, which is socializing. Katazyna [14] conducted a study and found that having a proper space is important as students need to socialize such as to study, talk, or have fun together. Most students value their friendships through face-to-face socializing in order to have real connections. Afsoon and Farah [15] concluded that evaluation of housing correlated to other tenants' personality as the social factor is crucial in residency as well as to be able to communicate with others despite modernization in these current years.

Another issue that has been a great concern regarding living off-campus is the facilities provided such as Wi-Fi, bedroom, bathroom, toilet, living area, kitchen, and access to other facilities like shops, or other technology like television and refrigerator. Besides, living off-campus might cause problems such as privacy, neighborhood disputes, severed landlord's relationship, noise problem, environmental pollution, shortage of water, disputes over payment of monthly electricity and water bills [16]. Muhammad et al. [17] studied the challenges faced by the non-resident students with regard to off-campus living environment. The result showed that the students are concerned about services factors and community facilities such as parking space, public transport and sport complex for recreational activities. The second highest factor that becomes a concern to non-resident students is that they are not comfortable enough and living conditions remain unsecured.

Privacy is also another important factor. It is the state of being free from any disturbance in one's private life or freedom to be alone. Solitude is being alone and free from others' eyes and can be viewed as a kind of privacy. Katarzyna [14] showed that a double room followed closely by a single room and renting the entire flat is the most common choice among Polish students to have privacy.

The awareness of physical and social factors perhaps would help non-resident students to consider renting a house. This study also tries to provide awareness to the landlords of the factors that should be improved in order to attract students to rent their house. This motivates the researchers to explore the factors that might affect the demand and value of student rental housing using data mining. Thus, this study helps to determine the factors which have an impact on the rental housing value and to identify the best combination of factors using data mining approach. This method can explore underlying patterns and rules to predict the outcome. By investigating the rental housing value among three public universities located in Kelantan, Malaysia, this study aims to study the factors affecting student rental housing value among public university students in Kelantan and identify the preferred characteristics of rental house. Students from three public universities were randomly chosen to be involved in this study.

2 MATERIAL AND METHODS

2.1 Study Design and Data

A cross-sectional study design was used and it is ideally suited because all information regarding the factors that affect the number of rental houses is gathered once. The population is undergraduate students from three local universities in Kelantan which are Universiti Teknologi MARA (UiTM), Universiti Malaysia Kelantan (UMK) and Universiti Sains Malaysia (USM). The number of population for students in UiTM, UMK, and USM is 7729, 9000 and 8375, respectively. The information is obtained from the university website. The students came from diverse backgrounds in terms of age and universities. Stratified random sampling technique with three strata which are UiTM, UMK and USM was used. Each stratum consisted of 7729, 9000 and 8375 students respectively. Probabilities sampling techniques was used to select a sample and the sample size was calculated by using Raosoft calculator with 5% margin of error and 95% confidence interval. A sample of 377 students were selected at random proportionately from each university to answer the survey. A total of 117 students were selected from UiTM, 136 students from UMK, and 124 students from USM. The selection of respondents within the strata was chosen randomly. This study obtained ethical approval from the Research Ethics Committee with registered approval number REC/04/2021 (UG/MR/329).

2.2 Instrument and Data Collection

Self-administrated questionnaire was used as an instrument tool to collect the data which contained 5 sections. This study used a structured questionnaire adopted from Hart Research Associates [18]. Section A is about Demographic profile while Section B is on Agreement on Rental Fee. The third section is Section C which is Agreement on Facilities and Section D is Agreement on Socializing. Next, Section E is about Agreement on Privacy, Section F is on Rental value, while Section G and H describe the Facilities Characteristics. 7-point Likert scale was used in Section B to Section E. The score depends on how highly the respondents disagree and agree with the statement. Rental values are measured as categorical value with high and low value, while section G and H are measured as dichotomous scale of having or not having the respective facilities. Data were collected from the respondents using google form. The questionnaire was distributed to the selected respondents via WhatsApp.

2.3 Statistical Analysis

2.3.1 Descriptive Analysis

Descriptive analysis is used to describe the characteristics of the variables because it helps to identify the important component of this analysis and predictive modeling to describe the relationship between factors influencing the rental housing demand. Descriptive statistics are used to present quantitative explanations in a manageable form [19]. In a sensible way, it helps to simplify massive amounts of data. Mean, standard deviation, variance, minimum and maximum value from the data was used to describe the variable and the results are displayed in summary statistics.

2.3.2 Data Mining Methodology

Data mining method was used in the study. Data mining is one of the methods that is used to obtain useful knowledge from complex and vast amounts of data [20]. There are five phases in the data mining process which are identification of problem, preparing the data, establishing and evaluating the model, using the model and monitoring the model [21].

In the first step, identifying the problem involves determining the existence of relationship between data on physical and environmental characteristics of housing and social and rental values. If there is any relationship, the relationship can be successfully modeled and identified. Guided from this, the data to be collected are drafted using a questionnaire and used to solve this problem. Next, data are collected and pre-processed for any missing values or extreme cases. In the data preparation stage, to comply with the WEKA and SPSS used in data mining practice, headings are converted to a style without spaces. Model establishments are carried out using supervised data mining approach such as decision tree algorithms and artificial neural network models. To ensure the validity of the model, this study used 10-fold cross-validation for both decision tree algorithms and artificial neural network models. Then, the models produced are interpreted and the output shown is presented.

2.4 Predictive Modelling

2.4.1 Decision Tree

Decision Tree Mining is a type of technique for data mining that is used to create classification models. In the form of a tree-like structure, the algorithm constructs classification models to classify the target variable into categories. This type of data mining approach is one of supervised class learning. Decision tree can also be interpreted as a special form of a rule set, characterized by their hierarchical organization of rules [22]. CHAID and CART are the two oldest types of Decision trees. They are also the most common types of Decision trees used in the industry today as they are super easy to understand while being quite different from each other.

2.4.1.1 CART

The classification tree construction by CART is based on binary splitting of the attributes. It is also based on Hunt's algorithm which can be implemented serially. It uses Gini index splitting measure in selecting the splitting attribute. CART algorithm of Gini coefficient is used intuitively for a purpose such as making use another criterion to split the nodes. The formula of Gini coefficient in Equation (1) is as follows;

$$GINI(t) = \sum_k [p(C_k|t)^2] \tag{1}$$

$p(C_k|t)$ is the probability of a node t being the category C_k. The Gini coefficient of the node t is 1 minus the sum of the probability of all categories.

2.4.1.2 ID3

ID3 is another type of decision tree algorithm, also known as Iterative Dichotomiser 3, which is used to generate a decision tree from the dataset. ID3 algorithm uses entropy to calculate the homogeneity of a sample. If the target variable takes on 'c' different values, then entropy relative to the c-wise classification is defined as;

$$Entropy(s) = \sum_{i=1}^{c} -P_i log_2 P_i \tag{2}$$

Where P_i is the probability of S belonging to class i logarithm which is base 2. If entropy E(s) = 0, it means that it is completely homogenic or we can say that it is leaf node of tree which cannot be divided further. ID3 also uses lowest entropy in order to split the algorithm.

2.4.2 Artificial Neural Network (ANN)

Categories of ANN are based on supervised and unsupervised learning methods. The simplest form of ANN architecture is the perception, which consists of one neuron with two inputs and one output. The network involves the activation function used which is step function or ramp function. Perceptions are used to classify the data into two separate classes. For more complex applications, multilayer perceptions (MLP) are used, which contain one input layer, one output layer, and one or more hidden layers.

2.4.3 Model Evaluation

Model evaluation is an integral part of the model development process. It helps to find the best model that represents the data and how well the chosen model will work in the future. This study used 10-fold cross validation. To avoid overfitting, all algorithms use a test set (not seen by the model) to evaluate model performance. The models are evaluated using sensitivity, specificity and accuracy measures.

2.4.3.1 Sensitivity

The proportion of positives that are correctly detected is measured by sensitivity (True Positive rate). This can be expressed mathematically in Equation (3) as:

$$\text{Sensitivity} = \frac{\text{True Positive}}{(\text{True Positive} + \text{False Negative})} \tag{3}$$

2.4.3.2 Specificity

The proportion of negatives accurately detected (i.e., the proportion of individuals who do not have the condition (unaffected) who are correctly identified as not having the ailment) is known as specificity (True Negative Rate). Calculate the fraction of true negatives in healthy instances to estimate it. This can be expressed in Equation (4):

$$\text{Specificity} = \frac{\text{True Negative}}{(\text{True Negative} + \text{False Positive})} \tag{4}$$

2.4.3.3 Accuracy

Accuracy is measured as the proportion of correctly categorized individuals among all subjects and is sometimes referred to as "diagnostic accuracy" or "diagnostic efficacy". We should determine the fraction of true positive and true negative in all analysed cases to estimate a test's accuracy. This can be expressed mathematically in Equation (5):

$$\text{Accuracy} = \frac{(\text{True Negative} + \text{True Positive})}{(\text{True Negative} + \text{True Positive} + \text{False Negative} + \text{False Positive})} \tag{5}$$

3 RESULTS AND DISCUSSION

3.1 Descriptive Statistics

A total of 377 respondents involved in this study were from Universiti Teknologi MARA (UiTM), Universiti Malaysia Kelantan (UMK) and Universiti Sains Malaysia (USM). Figure 3.1 shows that the proportion of the student placement from the three universities is almost proportionate. About 31.03% (117) students were from Universiti Teknologi Mara (UiTM), 36.07% (136) students were from Universiti Malaysia Kelantan (UMK) and 32.89% (124) were from Universiti Sains Malaysia (USM). Majority of the respondents were female with 68.44% (258) while only 31.56% (119) of the students were male (Figure 3.2). About 49.87% (188) of the students' age were in a range between 22 to 23 years old. This is followed by 36.07% (136) of students' age with the range of 20 to 21 years old and only 14.06% (53) students were 24 years old and above (Figure 3.3).

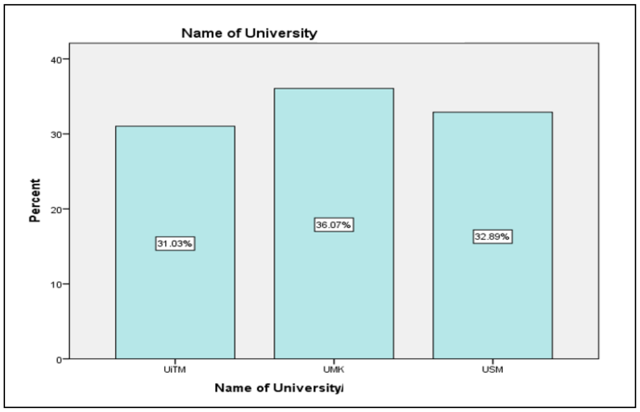

Figure 1: Distribution of students' university

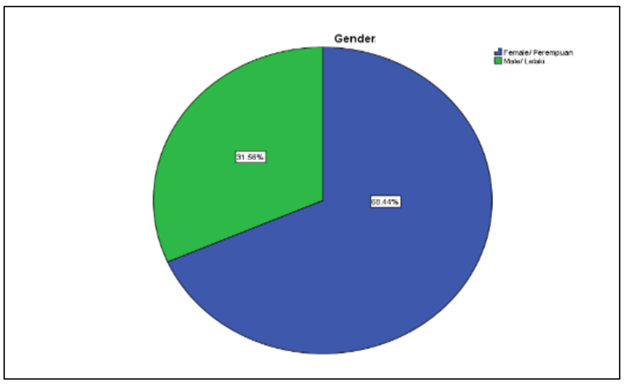

Figure 2: Pie chart of students' gender

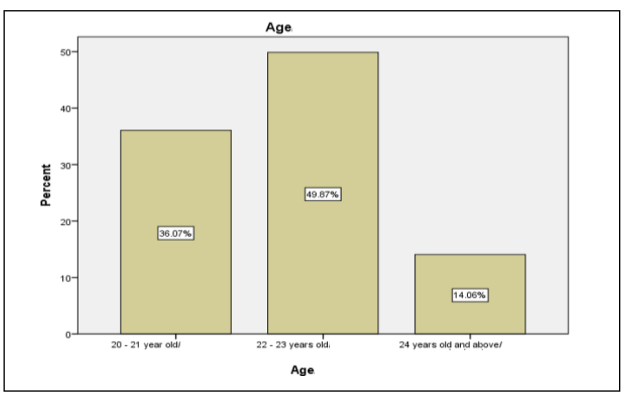

Figure 3: Distribution of students' age

Table 3.1 describes the result of mean analysis for the level of agreement on factors affecting rental housing. The analysis was conducted for each characteristics describing the agreement level on rental fee, facilities, socializing, privacy and rental price on the scale of 1= Highly agree to 7=Highly disagree. The mean level of agreement was calculated by taking the average score of each item obtained from the questionnaire. Based on the characteristics parameter in Table 3.1, most of the students agree that the rental fee of the house in Kelantan is affordable with the mean for affordable rental fee is (5.966±1.433). In terms of method of payment for rental fee, the mean levels of agreement to pay rental fee monthly, payment made by cash, payment made at bank and payment based on per individual rather than per house were (5.851±1.412, 4.809±2.096, 6.170±1.2874, 5.615±1.709) respectively. It can be seen that the students prefer to pay rental fees at the bank compared to cash.

For facilities characteristics, majority of the students highly agree that facilities are the most important factor that affects university student's rental house value since the overall mean for facilities shows the highest level of agreement which is (6.6211±0.7672). Students highly agree that all facilities of the rental house including television, kitchen space, parking lot, Wi-Fi, washing machine, clothes rack and fan affect university student rental house value. Overall, students agree with rental house value that is associated with socializing characteristics. The overall mean score on socializing factor for university student rental housing value gives the value of (5.9967±1.4023). The mean scores for renting house with many of their friends in it, rent house with friends as their roommates and house that allows friends to visit and sleep over are (6.601±1.3930, 5.944±1.4838, 6.019±1.3397 and 5.963±1.3929) respectively. Privacy factor gives a lower overall mean level of agreement with (4.8057±0.2493) which can still be classified as agree with a bit lower of value compared to other characteristics. Most of the students agree that they prefer to live in a single room as it is more private with the mean of (5.873±1.6916). Students also agree to live in a shared room with double decker and 'queen' size bed with the mean values of (4.973±2.087, 4.379±2.1418) respectively. However, students moderately agree nor disagree on living in a shared room with 6 people as it has the lowest mean score of (3.997±2.2697) which is below 4 score value. There is a high amount of variation in privacy followed by rental fee and socializing since the value of standard deviation is quite high for each item. However, facilities score indicates that the values tend to be close to mean of the data set as these variables show low standard deviation.

Table 1: Mean Analysis

Variable		**Mean**	**Standard Deviation**	**Mean level of agreement**
Independent Variable				
Overall Rental Fee		**5.6822**	**1.5878**	**Agree**
The rental fee is affordable		5.966	1.4334	Agree
I prefer to pay rental fee monthly		5.851	1.4120	Agree
I prefer to pay rental fee by cash		4.809	2.0963	Agree
I prefer to pay rental fee by bank		6.170	1.2874	Highly Agree
I prefer rental fee based on per individual rather than per house		5.615	1.7098	Agree
Overall Facilities		**6.6211**	**0.7672**	**Highly Agree**
I prefer rental house with television		6.154	1.3078	Highly Agree
I prefer rental house with kitchen space		6.655	0.6424	Highly Agree

I prefer rental house with parking lot		6.631	0.7851	Highly Agree
I prefer rental house with Wi-Fi		6.690	0.7414	Highly Agree
I prefer rental house with washing machine		6.793	0.5405	Highly Agree
I prefer rental house with clothes rack		6.668	0.7394	Highly Agree
I prefer rental house with fan		6.756	0.6136	Highly Agree
Overall Socializing		**5.9967**	**1.4023**	**Agree**
I prefer to rent a house with many of my friends in it		6.601	1.3930	Highly Agree
I prefer to rent a house with my friends as the roommates		5.944	1.4838	Agree
I prefer to rent a house that allows friends to visit		6.019	1.3397	Highly Agree
I prefer to rent a house that allows friends to sleep over		5.963	1.3929	Agree
Overall Privacy		**4.8057**	**0.2493**	**Agree**
I prefer to live in a single room		5.873	1.6916	Highly Agree
I prefer to live in a shared room with double decker		4.973	2.0870	Agree
I prefer to live in a shared room with a queen-size bed		4.379	2.1418	Agree
I prefer to live in a room that is shared by 6 people and above		3.997	2.2697	Disagree

3.2 Predictive Model For Rental Housing Value

Several predictive models namely Decision Tree of ID3, Decision Tree CART and Artificial Neural Network were fitted for the data set. The models fitting were carried out with 10-fold cross validation. The sensitivity, specificity and accuracy were calculated and tabulated in Table 3.2 below.

Table 2: Model Performance Evaluation

ALGORITHM	ACCURACY (%)	SENSITIVITY (%)	SPECIFICITY (%)
ID3 Decision Tree	78.82	87.45	60.66
CART Decision Tree	78.81	87.11	60.33
ANN	75.86	81.78	63.03

Referring to Table 3.2, Decision tree model ID3 algorithm gave the highest value of 78.82% accuracy which means the model is good. The accuracy of CART algorithm was a bit lower than ID3 which is 78.81% and artificial neural network had the lowest accuracy which is 75.86%. Based on Sensitivity value, the highest value of sensitivity was ID3 algorithm (87.45%), followed by CART algorithm (87.11%) and artificial neural network (81.78%). However, Artificial neural network had a slightly higher value which was 63.03% compared to the other two models for specificity. ID3 algorithm had a higher specificity than CART algorithm with the value of 60.66% and 60.33% respectively. Thus, based on this model performance comparison, Decision tree ID3 algorithm is the best model since the sensitivity and accuracy for decision tree ID3 algorithm is higher than CART algorithm and neural network model. Thus, the interpretation on the output is presented only for Decision Tree of ID3 Model.

For Decision tree ID3 algorithm, the model was fitted using information gain criterion. The entropies of all attributes are calculated and the one with the least entropy is selected for split. The output diagram of ID3 Decision tree algorithm is shown in Figure 3.4. Based on the figure, the most important variable in deciding whether the rental house gets a high or low value is having microwave based on the top node in the decision tree. The second most important factor in deciding whether the rental house gets a high or low value is whether the house has a single room and provides television. Meanwhile, the least important factor in determining whether the rental house gets a high or low value is the house location has difficult access to banking service.

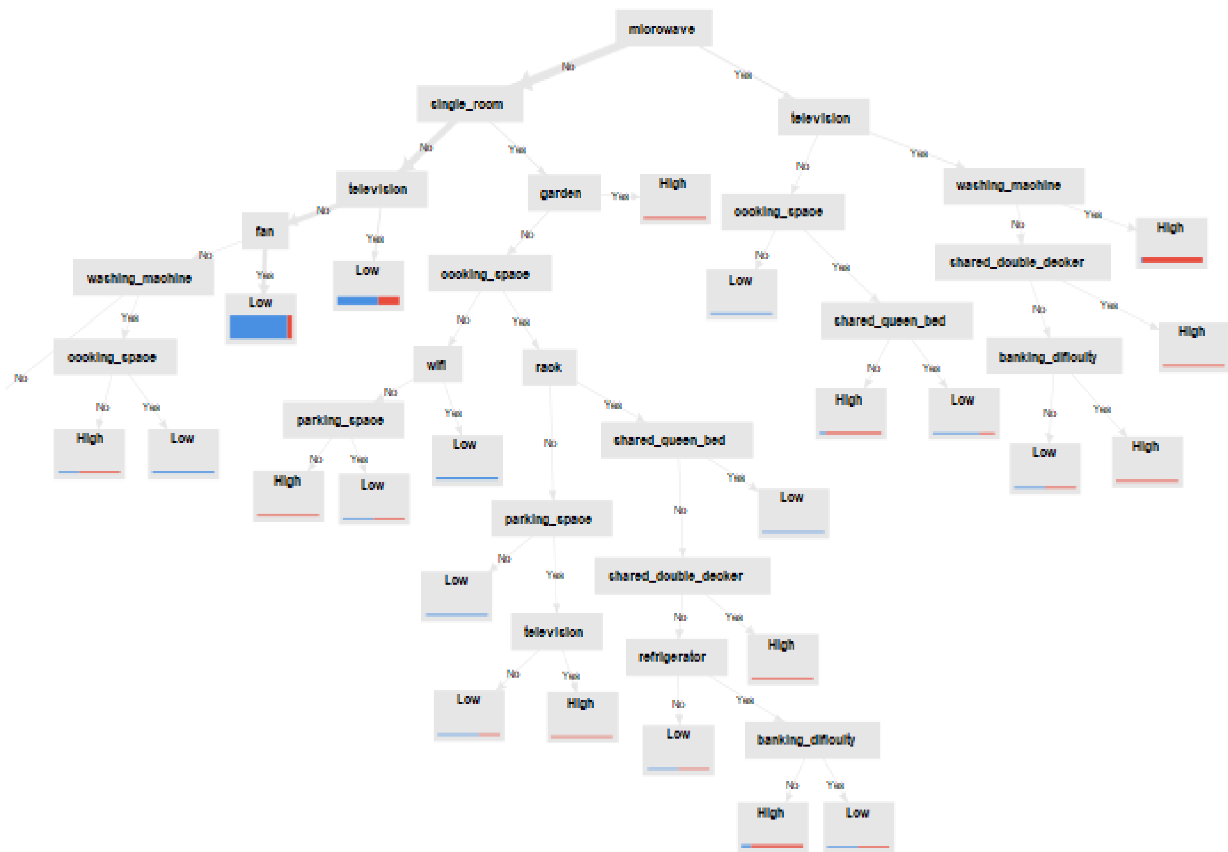

Figure 1: ID3 Decision Tree

Table 3.3 shows the significant rules that were extracted from the tree to predict the housing rental value using Decision Tree ID3. Based on Table 3.3, the rental house value is high when the house provides microwave, television and washing machine. A rental house has also high rental value if the house has single room although it does not have microwave, garden, cooking space or kitchen space, Wi-Fi and parking space. Another significant rule for high value rental housing is if the house has microwave, television and a shared room with double decker even though the house does not provide washing machine. Besides, if the house has a single room and garden but do not have microwave, the rental housing value is also high. The last significant rule for high value rental housing is when the house has microwave, no television, has cooking space and a shared room with queen bed.

For low rental value, if the house has no cooking space but has a microwave, the housing value is still low. Another rule is if the house does not have microwave, no single room and no television but has fan, then the rental housing value is low. Next, the low rental house also includes a house that has no microwave, no single room but has television. It is similar to a rental house that has no microwave, has single room, no garden, has cooking space, has rack and a shared room with queen bed. The last significant rule for a low value house is when a house has no microwave, has single room, no garden, no cooking space and has Wi-Fi. Thus, we can conclude that the high rental value house is those houses with many facilities and characteristics as compared to the low rental value house.

Table 3: Significance Rule Using DT ID3

No	Rule	Predict
1	If (Microwave = Yes) AND (Television = Yes) AND (Washing Machine = Yes) THEN (Rental Value = High)	Rental Value = High
2	If (Microwave = No) AND (Single Room = Yes) AND (Garden = Yes) THEN (Rental Value = High)	Rental Value = High
3	If (Microwave = Yes) AND (Television = Yes) AND (Washing Machine = No) AND (Shared double decker = Yes) THEN (Rental Value = High)	Rental Value = High
4	If (Microwave = Yes) AND (Television = No) AND (Cooking Space = Yes) AND (Shared queen bed = No) THEN (Rental Value = High)	Rental Value = High
5	If (Microwave = No) AND (Single Room = Yes) AND (Garden = No) AND (Cooking Space =No) AND (Wi-Fi = No) AND (Parking Space = No) THEN (Rental Value = High)	Rental Value = High
6	If (Microwave = Yes) AND (Cooking Space = No) THEN (Rental Value = Low)	Rental Value = Low
7	If (Microwave = No) AND (Single Room = No) AND (Television = No) AND (Fan = Yes) THEN (Rental Value= Low)	Rental Value = Low
8	If (Microwave = No) AND (Single Room = Yes) AND (Garden = No) AND (Cooking Space = No) AND (Wi-Fi =Yes) THEN (Rental Value= Low)	Rental Value = Low
9	If (Microwave = No) AND (Single Room = Yes) AND (Garden = No) AND (Cooking Space = Yes) AND (Rack = Yes) AND (Shared queen bed = Yes) THEN (Rental Value= Low)	Rental Value = Low
10	If (Microwave = No) AND (Single Room = No) AND (Television = Yes) THEN (Rental Value= Low)	Rental Value = Low

4 CONCLUSION

Data mining method is used to examine the factors affecting university student rental housing value in Kelantan. ID3 is the best model in determining the factors that significantly influence the rental value. The main important characteristics that determine the house rental value is the availability of facilities such as microwave followed by having a single room and a television. Most of the rental houses that are equipped with cooking space, rack, washing machine or Wi-Fi will be most likely to be equipped with fan. Moreover, the result of this study would help Malaysian universities develop more strategies or policies to help and cater the priorities to increase non-resident students' well-being. To achieve the vision and mission of globalizing the higher education in Malaysia, the needs of students should be continuously explored as student enrolment is increasing year by year. Thus, a proper solution for non-resident students is very important to support the students' lifestyle.

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REFERENCES

[1] "HE student enrolments by level of study 2016/17 to 2020/21," *HESA*. [Online]. Available: https://www.hesa.ac.uk/data-and-analysis/sb262/figure-3 [Accessed September 7, 2022]

[2] N. U. M. Najib, N. A. Yusof, and Z Osman, "Measuring satisfaction with student housing facilities," *American Journal of Engineering and Applied Sciences*, vol. 4, no. 1, pp. 52-60, 2011.

[3] "Number of students enrolled in public higher education institutions in Malaysia from 2012 to 2020, by gender", *Statistics yearbook Malaysia 2020*. [Online]. Available:https://www.statista.com/statistics/794845/students-in-public-higher-education-institutions-by-gender-malaysia/ [Accessed September 9, 2022]

[4] D. Hartman, "Student Housing Problems," *Home Guides SF Gate*, 2020. [Online]. Available: homeguides.sfgate.com/student-housing-problems-8397.html [Accessed September 7, 2022]

[5] M. Shirley, "The Effects of Overcrowding on Student Academic Performance in Kentucky High Schools," MPA/MPP/MPFM Capstone Projects. 283, 2017. [Online]. Available: https://uknowledge.uky.edu/mpampp_etds/283 [Accessed September 7, 2022]

[6] C. Zheng, "Non-local students, housing demand and rental impact: Evidence from mainland students in Hong Kong," *International Real Estate Review*, vol. 20, no. 4, pp. 525-548, 2017.

[7] S. Sen and N. Antara, "Influencing factors to stay off-campus living by students," *Journal of Philosophy, Culture and Religion*, vol. 38, 2018.

[8] S. Yunus, Y. A. Yusuf, S. K. Ilah, and M. D. Yakubun, "Spatial Analysis of Off-Campus Student Housing Around the New Campus of Bayero University," *Savanna*, *A Journal of the Environmental and Social Science*, vol 24, no. 2, pp. 359 – 371, 2018.

[9] D. B. Omar, F Abdullah, F. Yusof, H. Hamdan, N. Nasrudin, and I. C. Abdulalh, "The impacts of off-campus students on local neighbourhood in Malaysia," *International Journal of Educational and Pedagogical Sciences*, vol. 5, no. 10, pp. 1221-1227, 2011.

[10] F. Khozaei, N. Ayub, A. S. Hassan, and Z. Khozaei, "The factors predicting students' satisfaction with university hostels, case study, Universiti Sains Malaysia," *Asian Culture and History*, vol. 2, no. 2, pp. 148 - 158, 2010.

[11] P. S. K. Chi and M. D. Griffin, "Social indicators for measuring residential satisfaction in marginal settlements in Costa Rica," *Social Indicators Research*, vol. 8, no. 4, pp. 453-465, 1980.

[12] J. Yuan, X. Zheng, J. You, and M. J. Skibniewski, "Identifying critical factors influencing the rents of public rental housing delivery by PPPs: the case of Nanjing," *Sustainability*, vol. 9, no. 3, p. 345, 2017, doi:10.3390/su9030345.

[13] J. U. Adama, D. O. Aghimien, and C. O. Fabunmi, "Students' housing in private universities in Nigeria: influencing factors and effect on academic performance," *International journal of built environment and sustainability*, vol. 5, no. 1, 2018.

[14] K. Bozena Strzalka, "What are the Students' Housing Preferences? A Case Study of Lublin, Poland," Dissertation, 2019. [Online]. Available: http://urn.kb.se/resolve?urn=urn:nbn:se:kth:diva-254819 [Accessed September 7, 2022]

[15] M. Afsoon and H. Farah, "Explaining the role of cultural, social and economic factors on quality of residence in urban neighborhoods: A case study of Kerman," *Journal of Geography and Regional Planning*, vol. 9, no. 5, pp. 59-69, 2016.

[16] I. Addai, "Problems of non-residential students in tertiary educational institutions in Ghana: a micro-level statistical evidence," *Journal of Emerging Trends in Educational Research and Policy Studies*, vol. 4, no. 4, pp. 582-588, 2013.

[17] M. H. Muslim, H. A. Karim, and I. C. Abdullah, "Challenges of off-campus living environment for non-resident students' well-being in UiTM Shah Alam," *Procedia-Social and Behavioral Sciences*, vol. 50, pp. 875-883, 2012.

[18] *MacArthur How Housing Matters Survey*, Hart Research Associates, April 2014. [Online]. Available: https://www.macfound.org/media/files/HHM_Hart_data_2014.pdf [Accessed September 7, 2022].

[19] W. M. K. Trochim and J. P. Donnelly, *Research Methods Knowledge Base*, vol. 2. New York: Atomic Dog Pub, 2001.

[20] A. Lausch, A. Schmidt, and L. Tischendorf, "Data mining and linked open data–New perspectives for data analysis in environmental research," *Ecological Modelling*, vol. 295, pp. 5-17, 2015.

[21] R. M. Alford, "Shear Data in the Presence of Azimuthal Anisotropy: Dilley, Texas," *SEG Technical Program Expanded Abstracts*, pp. 476-479, 1986.

[22] J. Jackson, "Data mining; a conceptual overview," *Communications of the Association for Information Systems*, vol. 8, no. 19, pp. 267-296, 2002.